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The Use of Commodity Futures Momentum in Momentum Portfolio Diversification

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ABSTRACT:

Commodity futures have gained popularity as an investment vehicle since the early 2000s. On their own, commodity futures are considered a volatile asset class. However, due to their low correlation with other assets, such as equities, they are often found to enhance the risk-return characteristics of equity portfolios.

This Master's thesis examines whether the diversification benefits from including commodity futures in the regular long equity portfolios are applicable to momentum strategies implemented on the two asset classes. Furthermore, this thesis examines if the inclusion of commodity futures momentum in an equity momentum portfolio influences the severity momentum crashes experienced during market distress.

By using a 30-year (1990-2019) return series on two momentum strategies implemented on equities and commodity futures, an in-sample optimal portfolio is constructed. Furthermore, a beta hedging procedure is implemented on the two individual momentum strategies and an optimal portfolio out of the two hedged strategies is constructed.

To find whether the individual strategies or portfolios pose abnormal returns, multivariate regressions utilizing Fama-French Three and Six Factor Models are run. Additionally, to see whether the diversified portfolios are less exposed to momentum crashes, an optionality regression is run. Equity momentum returns are found to be influenced by the overall equity market risk and liquidity. To see whether the diversified portfolios are less affected by these factors, a regression applying proxies for risk and market liquidity is run.

The constructed optimal portfolios pose lower annualized volatilities and higher cumulative returns when compared to the individual momentum strategies. Additionally, when comparing to the pure equity momentum strategies, the diversified portfolios pose significantly fewer large drawdowns. However, due to high standard errors, there is no statistical difference between the Sharpe ratios of the diversified portfolios and their pure equity momentum counterparts. Furthermore, much like the individual momentum strategies, the diversified portfolios do not pose significant abnormal returns when corrected for the Fama-French six risk factors. Lastly, the diversified portfolios are not statistically less exposed to momentum crashes.

KEYWORDS: Momentum, commodity futures, portfolio theory, diversification, momentum crashes

VAASAN YLIOPISTO
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TIIVISTELMÄ:

Hyödykefutuurit ovat keränneet suosiota sijoituskohteena jo 2000-luvun alusta. Itsessään futuurit ovat riskinen sijoituskohde. Kuitenkin futuurien ja muiden omaisuusluokkien välinen korrelaatio on matala, minkä vuoksi futuureja käytetään hajautusvälineenä. Hyödykefutuurien lisäys tavalliseen osakeportfolioon usein parantaa portfolion riski-tuotto-suhdetta.

Tässä tutkielmassa tarkastellaan, voidaanko hyödykefutuurien sisällyttämisestä tavallisiin osakeportfoliohin koituvia hajautushyötyjä soveltaa myös näihin kahteen omaisuusluokkaan toteutettuihin momentum-sijoitusstrategioihin. Lisäksi tutkielmassa tarkastellaan, ovatko hajautetut osake-hyödyke-momentum portfoliot lievemmin altistuneita momentum-romahduksille, jotka ovat suuri riskin lähde osakkeisiin sijoittaville momentum-strategioille.

Tutkielman portfolioiden muodostamisessa käytetään tuottodataa kolmenkymmenen vuoden ajalta (1990–2019) hyödykefutuureihin ja osakkeisiin sijoittavista momentum-strategioista. Portfoliot muodostetaan tavalla, joka maksimoi otoksen Sharpen-luvun. Lisäksi kahteen mainittuun momentum-strategiaan sovelletaan beta-suojausstrategiaa. Suojausstrategian lopputulemana saadaan kaksi beta-suojattua momentum-strategiaa, joista muodostetaan portfolio painoilla, jotka maksimoivat otoksen Sharpen-luvun.

Yksittäisten strategioiden ja portfolioiden epänormaaleja tuottojen tutkimiseen käytetään Fama-French -faktorimalleja. Lisäksi yksittäisten strategioiden sekä hajautettujen portfolioiden altistumista momentum-romahduksille tutkitaan käyttämällä vaihtoehtoisuusregressiota (*optionality*). Markkinalikviditeetti sekä -riski vaikuttavat merkitsevästi osake-momentumin tuottoihin. Näiden tekijöiden vaikutusta hajautettuihin portfolioihin tutkitaan käyttäen regressiota, joka soveltaa riskitekijöitä edustavia muuttujia.

Rakennettujen portfolioiden volatiliteetti on tilastollisesti pienempi verrattuna pelkkiin osake-momentum-strategioihin. Lisäksi portfolioiden kumulatiiviset tuotot ovat suurempia kuin yhdenkään yksittäisen hyödykefutuureihin tai osakkeisiin sijoittavan momentum-strategian. Yksittäisiin momentum-strategioihin verrattuna portfoliot kohtaavat myös huomattavasti vähemmän suuria kuukausittaisia arvonalenemia. Kuitenkin suurien keskivirheiden vuoksi erot Sharpen-luvuissa portfolioiden ja osakkeisiin sijoittavien momentum-strategioiden välillä ovat tilastollisesti merkityksettömiä. Rakennetut portfoliot eivät myöskään tuota tilastollisesti merkittäviä epänormaaleja tuottoja. Hajautuksesta huolimatta portfoliot säilyttävät tilastollisesti altistumisensa momentum-romahduksille, vaikkakin portfolioiden romahdukset ovat tällä aikaperiodilla absoluuttisesti pienempiä.

AVAINSANAT: Momentum, hyödykefutuurit, portfolioteoria, hajautus, momentum-romahdukset

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1 Introduction

Before the 1950s investors had no tangible theory explaining the benefits of diversification. Markowitz (1952) revolutionized the world of Finance through the introduction of the Modern Portfolio Theory. The theory emphasizes the importance correlation (covariance) in portfolio construction. When considering a portfolio, the individual asset variances are of little importance; the risk to return ratio of a portfolio can be greatly improved through the inclusion of assets weakly co-varying with one another. (Markowitz, 1952.)

Commodity futures are often considered a speculative and a highly volatile asset class. In addition to their risk, commodities as real assets do not generate income streams, commodities often generate negative cashflows through storage costs. However, regardless of the downsides of real assets, commodity futures pose adequate yearly returns, nearly comparable to those of equities (Ankrim & Hensel, 1993; Bhardwaj, Gorton & Rouwenhorst, 2015). In addition to the equity-like returns, commodities pose low to negative correlations towards more traditional asset classes, such as equities or fixed income instruments (Ankrim & Hensel, 1993; Gorton & Rouwenhorst 2006). Considering the above-mentioned, it is no surprise that commodities are often used as tools of diversification. Commodities improve the risk-adjusted performance of more traditional portfolios consisting out of equities and bonds (Jensen, Johnson & Mercer, 2000).

Most often portfolio formation is done through taking only long positions in assets such as equities and commodity futures. However, the digitalization the financial markets has opened several other possibilities. Near instantaneous transactions, low transaction costs and increased computing power have created possibilities for computerized trading strategies based on the quantitative properties of the underlying assets. A widely known example of such trading strategies is momentum, first introduced in academic research by Jegadeesh and Titman (1993).

Ever since the paper of Jegadeesh and Titman (1993) momentum has become a widely known anomaly and a successful trading strategy in the global financial markets. momentum strategies bet on the continuation of the recent price performance; the strategies go long (short) on the best (worst) performing assets in the selected sampling period – initially forming a zero-cost portfolio. Due to this, the strategies are often by construction market neutral and thus several risk factor models are unable to explain the persistent, substantial returns posed by the strategies (Jegadeesh & Titman, 1993; Rouwenhorst, 1998; Asness, Moskowitz & Pedersen, 2013). Momentum is considered a global and a cross asset class anomaly; it is also present in the commodity futures markets. While having slightly elevated volatilities, momentum strategies implemented on commodity futures pose similar returns to their equity counterparts (Miffre & Rallis, 2007; Asness et al. 2013; Chaves & Viswanathan, 2016).

However, occasionally momentum strategies go through disastrous crashes, which wipe out majority of the invested capital and thus the profits made prior. These crashes are mutual for both momentum variants; however, the magnitude of the equity momentum crashes is vastly larger (Fuertes, Miffre & Fernandez-Perez, 2015; Daniel & Moskowitz, 2016). The underlying crash risk is often present in the return distribution of an equity momentum strategy, which poses heightened kurtosis and negative skewness (Barosso & Santa-Clara, 2015; Ruentzi & Weigert, 2018). The return distribution of a momentum strategy investing in commodity futures also experiences heightened kurtosis; however, the distribution's skewness is near-zero, or in some cases positive (Fuertes et al., 2015). Momentum crashes may be mitigated with different risk management methods such as volatility scaling (Barosso & Santa-Clara, 2015). The crashes may also be dampened if one introduces an uncorrelated asset into the portfolio. This method works if the uncorrelated asset does not experience a crash or experiences it during a different period.

1.1 Purpose

The purpose of this thesis is to find whether the performance of an equity only momentum portfolio can be improved by diversifying some of the portfolio in a momentum strategy implemented on commodity futures. This requires the correlation between the two strategies reside below one.

Commodity futures pose a 0.17 correlation towards equity momentum strategies (Asness, Ilmanen, Israel & Moskowitz, 2015). Such finding suggests that a momentum strategy implemented on commodity futures may also pose a near-zero correlation towards its equity counterpart. This is indeed confirmed by the findings of Asness et al. (2013) which affirm the cross-strategy correlation to be 0.20. As further discussed in Chapter 2.1., such correlation may already provide significant diversification benefits resulting in vastly improving portfolio performance. However, the current literature does not examine the performance of a momentum portfolio containing both equity and commodity futures momentum strategies. This thesis aims to contribute to the existing literature by examining the possible diversification benefits obtained from the formation of such portfolio.

Additionally, this thesis aims to uncover whether the dual momentum portfolios experience dampened momentum crashes. This requires the commodity futures momentum strategy to be uncorrelated to its equity counterpart during such times. Such behaviour is already hinted by the findings of Fuertes et al. (2015). In midst of the Financial Crisis of 2008, the S&P GSCI (a major commodity index) experiences a crash of 60%. However, the return on a commodity futures momentum strategy is largely left unaffected by the crisis years (2008-2009). During the same period, regular equity momentum strategies experience large monthly drawdowns nearing 45%, ultimately wiping out nearly 80% of the strategy cumulative returns within a timeframe of 14 months (Daniel & Moskowitz, 2016).

These objectives are assessed through examining the returns on two dual momentum portfolios. One of the portfolios is constructed out of plain, unhedged momentum strategies, the other contains strategies which are beta hedged following the example of Grundy and Martin (2001). This risk management method is chosen due to its ability to improve the overall performance of a momentum portfolio (Grundy & Martin, 2001). Additionally, a beta hedging procedure is easily implementable in real-world scenarios – even by individual investors through the usage of various ETFs following the factors being hedged.

1.1.1 Research Hypotheses

Three hypotheses are formed based on the objectives of the thesis. The first hypothesis concerns the profitability of momentum strategies implemented on commodity futures. This hypothesis is already proven true on data prior to 2011 (Miffre & Rallis 2007; Asness, et al., 2013). However, this thesis uses an eight year longer sampling period ending in 2019, thus, the hypothesis must be reassessed.

> ***H_1:*** Momentum strategies implemented on commodity futures produce statistically significant excess returns.

The second hypothesis concerns the possible diversification benefits obtained from the inclusion of a commodity futures momentum in an equity-only momentum portfolio. The hypothesis is tested with the change in the portfolio's Sharpe ratio in addition to the change in the portfolio alpha.

> ***H_2:*** The inclusion of commodity futures momentum influences the risk-adjusted performance of an equity-only momentum portfolio.

The last hypothesis investigates whether some variation of commodity futures momentum may influence the momentum crashes experienced during the 2000s. This is tested through examining the strategy-portfolio return distributions in addition to running an optionality regression first proposed by Daniel and Moskowitz (2016).

> ***H_3:*** The inclusion of a commodity futures momentum strategy affects the severity of a momentum crash.

1.2 **Structure of the Thesis**

This thesis is divided into eight chapters. After the introduction, the second chapter discusses Markowitz' (1952) Portfolio Theory, especially pinpointing the importance of cross-asset correlation in portfolio diversification. Momentum strategies are implemented on historical return performance; thus, it is important to examine how prices (returns) of equities and commodity futures are determined – this is the purpose of chapters three and four.

The fifth chapter examines momentum through reviewing prior research on the phenomenon. Most importantly, the latter part of the chapter examines the prevalence of momentum in the commodity futures markets in addition to examining the nature of momentum crashes, which are a major source of risk for the strategy.

The sixth chapter describes the data and methodology used in the empirical part of this thesis. Chapter seven contains the results based on the empirical analysis undertaken, additionally this chapter contains the interpretation and discussion of the results. The final chapter will conclude the thesis and summarize the main findings.

2 Portfolio Theory

The Modern Portfolio Theory introduced by Markowitz (1952) is one of the backbones of modern Finance. Before its inception there was no theoretical background for the portfolio formation process nor the benefits of diversification. The theory builds upon the assumption that investors seek to maximize their expected returns and minimize their risk (variance) during portfolio formation. Markowitz' findings on concepts like the Efficient Frontier and the importance of diversification revolutionized the world of Finance.

This chapter lays out the foundation for understanding the importance of cross-asset correlation in portfolio risk management. These principles are then used in the empirical part of this thesis where the dual strategy momentum portfolios are formed.

2.1 Principles

At the start of the portfolio selection process, an investor first considers the expected returns on all available assets. The expected returns on equities arise from the change in prices and the cashflows to the investor. In addition to other factors, such as market sentiment or liquidity, the expected cashflows are a key driver of equity prices. These cashflows may be considered random variables, as they ultimately depend on how the underlying business is faring (Huang, 2010). Therefore, the expected return of an asset is the sum of the returns during all the different outcomes (r_i) times the respective probability of their occurrence (P_{ij}) (Bodie, Kane & Marcus, 2015).

$$E(r_i) = \sum_{J=1}^{N} P_{ij} r_{ij} \tag{1}$$

As a portfolio is a combination of different assets with varying weightings, the expected return of a portfolio is the sum of the returns on all the assets (r_{ij}) times their individual weightings (w_{ij}):

$$E(r_P) = \sum_{J=1}^{N} w_{ij} r_{ij} \tag{2}$$

As the returns on assets rise from a multitude of different scenarios, there is inherent uncertainty present in the asset selection process. This uncertainty must be modelled for the portfolio selection process. This can be done with variance or its square root, standard deviation, both of which measure the dispersion around the mean – here the average expected return.

Variance is the expected value of the squared deviations from the expected return. In the case of a single asset, it is expressed as follows:

$$\sigma_i^2 = \sum_{J=1}^{N} P_{ij} [r_i - E(r_i)]^2 \tag{3}$$

where P_j is again the probability of the outcome, r_i is the return from the occurrence of the outcome and $E(r_i)$ is the expected return of the asset**.** The square root of variance, standard deviation (later regarded as volatility) is often used as a measure of risk in Finance. (Bodie et al. 2015.)

$$\sigma_i = \sqrt{\sigma_i^2} \tag{4}$$

Unlike the expected return of a portfolio, the variance of a portfolio is not equal to the weighted sum of the individual asset's variances. In the case of a two-asset portfolio, the variance can be expressed as follows:

$$\sigma_P^2 = W_1^2 \sigma_1^2 + W_2^2 \sigma_2^2 + 2W_1 W_2 \sigma_{12} \tag{5}$$

where W_i^2 are the squared weights for both assets and σ_i^2 are the asset specific variances. σ_{12} is the covariance between the two assets, it measures the co-variation of the individual asset variances. The latter term including covariance is a major component of the entire portfolio variance. Covariance is the product of the correlation between the assets (ρ_{12}) and the individual asset volatilities (σ_i):

$$\sigma_{12} = \rho_{12}\sigma_1\sigma_2 \tag{6}$$

Correlation gets values between -1 and +1. Thus, one can notably reduce the risk of an investment portfolio through introducing assets with low (negative) correlations. This is possible even through introducing riskier assets if these assets are not perfectly correlated with the other assets the portfolio (Markowitz, 1952).

If the correlation between the assets if perfectly negative (ρ_{12}= -1), one can nullify the portfolio risk by weighting the assets correctly. However, the portfolio variance becomes the weighted average of the individual asset variances if the assets are perfectly correlated with one another (ρ_{12}= +1). A zero correlation between the assets makes the portfolio variance lower than either one of the individual asset's variances. The above-mentioned can be proven as follows:

First, the investor is required to be fully invested in the two available assets (W_1+ W_2 = 1), thus, the weighting of the second asset is:

$$W_2 = 1 - W_1 \tag{7}$$

Now W_2 in Equation 8 can be substituted with the expression above. Additionally, the covariance term in the same equation is substituted with the expression in Equation 6. After these adjustments, the two-asset portfolio's variance is obtained as follows:

$$\sigma_P^2 = W_1^2\sigma_1^2 + (1 - W_1)^2\sigma_2^2 + 2W_1(1 - W_1)\rho_{12}\sigma_1\sigma_2 \tag{8}$$

If the two assets are *perfectly correlated* (ρ_{12}= 1) the expression above becomes:

$$\sigma_P^2 = W_1^2\sigma_1^2 + (1 - W_1)^2\sigma_2^2 + 2W_1(1 - W_1)\sigma_1\sigma_2 \quad (9)$$

The latter term may be rewritten as $W_1\sigma_1 + (1 - W_1)\sigma_2$ thus making the portfolio variance:

$$\sigma_P^2 = W_1^2\sigma_1^2 + (1 - W_1)\sigma_2^2 \quad (10)$$

which is simply the weighted average of the individual variances for the two assets (Elton et al., 2009).

A perfect negative correlation (ρ_{12}= -1) transforms Equation 8 into the following form:

$$\sigma_P^2 = W_1^2\sigma_1^2 + (1 - W_1)^2\sigma_2^2 - 2W_1(1 - W_1)\sigma_1\sigma_2 \quad (11)$$

Rewriting the latter term makes the equation:

$$\sigma_P^2 = W_1^2\sigma_1^2 - (1 - W_1)\sigma_2^2 \quad (12)$$

which allows the investor to completely nullify the portfolio risk by solving for a correct weighting for either one of the assets. The weighting that nullifies the portfolio variance for the first asset is:

$$W_1 = \frac{\sigma_2}{\sigma_2 + \sigma_1} \quad (13)$$

If the assets are uncorrelated with one another (ρ_{12}= 0) the last term in Equation 8 becomes a zero; thus, the portfolio variance can be expressed as:

$$\sigma_P^2 = W_1^2\sigma_1^2 + (1 - W_1)^2\sigma_2^2 \quad (14)$$

which by construction is lower than either one of the individual asset variances (Elton et al., 2009).

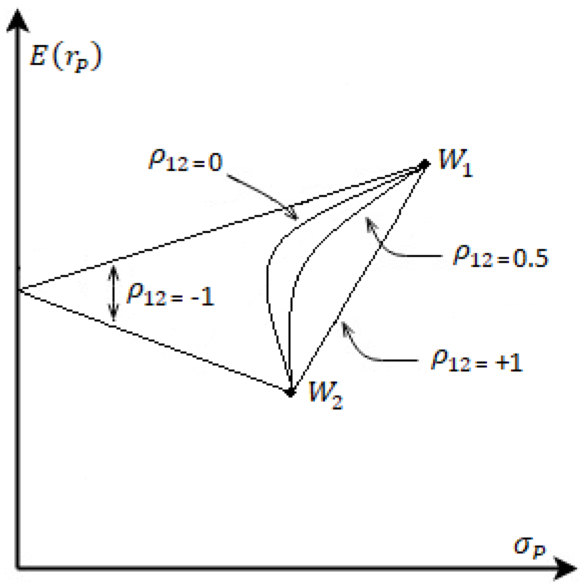

Figure 1. The importance of correlation (Elton et al., 2009)

Figure 1 illustrates the importance of correlation in the diversification of a two-asset portfolio. As shown earlier, it is hypothetically possible to obtain a riskless portfolio, if one can find two assets which have a correlation coefficient of -1. However, such correlations quickly disappear in real world scenarios, as they create arbitrage opportunities for the market participants. If the assets are perfectly correlated, the risk to return ratio of the portfolio increases linearly, as there are no diversification benefits to be gained. Notable improvements to the portfolio’s risk are already available once the correlation between the assets is 0.5. Additionally, the performance of the portfolio increases significantly if there is no correlation between the assets. With a certain allocation, the portfolio will have lower variance than either one of the individual assets. It is of paramount importance to highlight that the individual asset variances do not matter at this point, the second asset could pose twice the variance as the first asset – the portfolio’s risk to return ratio will be greatly improved if the uncorrelated asset is introduced to it. (Elton et al., 2009.)

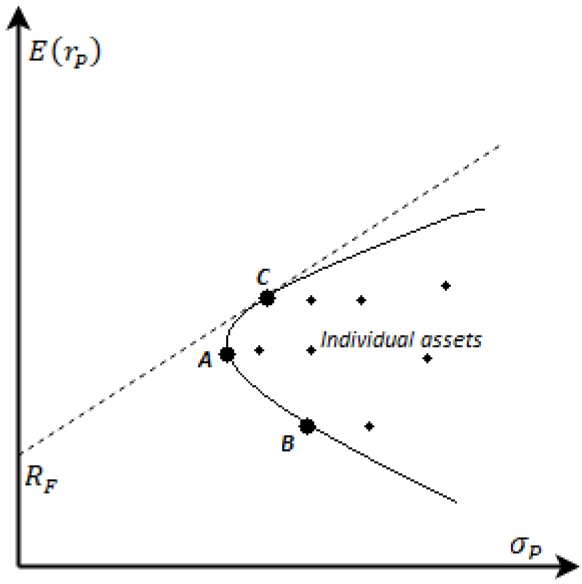

Figure 2. The efficient frontier (Bodie et al., 2014)

Figure 2 illustrates a situation that occurs in an asset universe where a risk-free return exists. Here, an investor has the opportunity to invest all of their capital into the individual assets or into a portfolio combining them. Choosing to invest in an individual asset would be suboptimal, as the investor could obtain a better return by combining them into a portfolio. The curved line illustrates the risk-return characteristics of the various portfolio choices. Portfolio A is the portfolio with the lowest risk (volatility). All the portfolio possibilities residing below this point (portfolio A) in the curve are considered inefficient as an investor could obtain a higher return with a lower. The part of the curve above the minimum variance portfolio (portfolio A) is called the *efficient frontier*, it contains the portfolio choices which provide the best possible returns for the given levels of risk. The optimal portfolio resides on the efficient frontier, it is the portfolio which has the highest Sharpe ratio. In the figure above the optimal portfolio is found by choosing the point where the efficient frontier is tangent with a line drawn from the risk-free return. (Bodie et al., 2014.)

The empirical part of this thesis forms portfolios out of momentum strategies. The portfolios are formed in a way which maximizes the in-sample Sharpe ratio. Thus, the portfolios under examination can be considered the optimal portfolios for the sample period.

3 Equities & Pricing Models

Momentum strategies are implemented based entirely on the past return performance of financial assets. Thus, it is important to understand the mechanics behind the price formation of these assets.

The chapter begins by defining the concept of market efficiency and then moves on to the basics of equity valuation. Finally, the chapter introduces the CAPM and the Fama-French Three, Five and Six Factor Models, which are further used in the empirical section of this thesis.

3.1 Market Efficiency

The purpose of capital markets is the allocation of the whole economy's capital stock, the functionality of these markets is vital for economic growth (Malkiel & Fama, 1970). In an ideal world, the capital stock moves freely out of doomed ventures to projects posing the highest utility available – ultimately leading to an improvement of the entire system. Asset prices provide signals for capital allocation. To achieve efficient allocation of capital, the available prices must fully reflect the information available (Malkiel & Fama, 1970).

The theory of market efficiency concerns the adoption of new and available information in asset pricing. In an efficient market, the prices of assets adjust instantaneously to new information, thus, all available information is embedded in the asset prices. Malkiel and Fama (1970) refer to this as the Efficient Market Hypothesis (EMH). The EMH is most often presented in three forms: the weak, semi-strong and strong (Bodie et al. 2014).

The weak-form of EMH asserts that the current asset prices reflect all available information which can be derived from past market trading data, such as historical asset prices. Opportunities to earn excess returns based on historical data are instantaneously undertaken, as such data is freely available to every market participant. The asset prices will instantaneously shift to their equilibrium as all the market participants are simultaneously competing for the opportunities to earn excess returns. In such markets technical analysis is without merit – however, some market participants may still beat the market through the adoption of other information. (Bodie et al. 2014) The weak-form market efficiency is most often supported by the available evidence (Malkiel & Fama, 1970). However, the evidence on the persistence of momentum returns is a direct violation of the weak-form EMH, as momentum strategies are solely implemented on past pricing data.

The semistrong-form of the hypothesis requires that all publicly available information be embedded in the asset prices. In addition to the historical market data, this information includes the fundamental data on the firm's business prospects (Bodie et al. 2014). In such market, fundamental analysis executed on the publicly available information is futile. Again, as the market participants are competing for the excess returns en masse, the changes in firm-level fundamental data, such as an increase in sales, gets instantaneously embedded in the asset prices. The semistrong-form of market efficiency is often considered the accepted paradigm (Jensen, 1978). However, it is also contested by the existence of several anomalies, such as the small firm effect (Stoll & Whaley, 1983).

In addition to everything set by the two earlier forms of EMH, the strong form asserts that current asset prices instantaneously adjust to all relevant available information– including insider information. This form of EMH is extreme and is considered more of a completion to the set of hypotheses than as an illustration of real world (Jensen, 1978).

Testing for market efficiency comes with its problems, as it must be tested jointly with an asset pricing model which often takes the form of a multivariate regression equation. To test whether the prices reflect the relevant information properly, one must construct a model which captures all the relevant information in its factors (Fama, 1991). Thus, evidence against market efficiency (the pricing model not explaining asset returns) may just be the cause of a poor pricing model – or it may be evidence on market inefficiency, naturally, it can also be both. This creates the problem on finding the optimal pricing model, which explains the anomalous returns no matter where they stem from. (Fama, 1991.)

This thesis directly tests the validity of the weak-form EMH in the equity and commodity futures markets. If the markets are weak-form efficient, momentum strategies should not pose statistically significant abnormal returns, as they are purely based on historical development of the asset prices. The next chapters introduce the reader to the asset pricing models used in testing for the abnormal returns.

3.2 Cashflow Models

At their core, equities are shares of operating companies. Thus, their intrinsic value can be derived from the sum of expected future cashflows for the company. The cashflows are discounted into present with an adequate rate which reflects the risk of the investment endeavour. When discounting cashflows to equity holders, such as dividends, the rate is the cost of equity. However, for discounting free cash flows (FCF) belonging to both equity and debt holders, a rate including the cost of debt is needed – most often the rate used is the weighted average cost of capital (WACC).

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t} \tag{15}$$

Apart from the discount rates, the mechanics do not differ between a regular dividend discount model (DDM) (equation 15) or a FCF-model (equation 16). However, the price proposed by the DDM is subject to changes in dividend policy and poorly suits companies paying little to no dividends. The FCF-model includes the whole available cashflow for the company debt- and shareholders, thus fitting well for all cashflow positive firms – regardless of the dividend policy. However, to arrive at a price per share, one must first deduct the net debt from the enterprise value (EV) and divide it with the total number of shares outstanding.

$$EV = \sum_{t=1}^{\infty} \frac{FCF_t}{(1+WACC)^t} \tag{16}$$

$$P_0 = \frac{EV - Net\ Debt}{Shares\ outstanding} \tag{17}$$

According to these models, the share prices fluctuate based on new information concerning the changes in variables which affect the future expected cashflows or dividends. Additionally, the share prices are inversely affected by the fluctuations in the discount rates. Investors demand a higher (lower) return for riskier (safe) ventures, thus driving the current share price down (up) with an increasing (decreasing) discount rate. In an efficient market the market prices reflect the changes in the variables instantaneously.

Considering the above-mentioned, in a frictionless market the returns of a momentum strategy should ultimately arise from changes in firm-level variables. However, recent literature finds no supportive evidence of this, the momentum puzzle is not explained by changes in firm-level variables (Bandarchuk & Hilscher, 2013).

3.3 **CAPM & Factor Models**

The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) aims to explain the relationship between the expected return and risk of an equity. The model is built upon two sets of assumptions concerning investor behaviour and the market structure:

Table 1. CAPM assumptions (Bodie et al. 2014)

1. **Individual behaviour**
   a. Investors are rational, mean-variance optimizers.
   b. Their planning horizon is a single period.
   c. Investors have homogeneous expectations (indentical input lists).
2. **Market structure**
   a. All assets are publicly held and trade on public exchanges, short positions are allowed, and investors can borrow or lend at a common risk-free rate.
   b. All information is publicly available.
   c. No taxes or transaction costs.

The model decomposes the expected return into two components: the market risk premium and the equities exposure to it. It is expressed as follows:

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f] \tag{18}$$

Where $E(r_i)$ is the expected return on an asset i, r_f is the risk-free rate, β_i is the asset's exposure to the market and $E(r_m)$ is the expected return for the market, making the term in the brackets the market's risk premium (Bodie et al., 2014).

CAPM has its flaws; it is often unable to properly capture expected returns. This may be caused by construction, as the model has only one proxy for risk (β_i). This naturally makes the model unable to explain returns for several long-short strategies (such as momentum), which are often market neutral (i.e. their beta towards the market portfolio nears zero) (Jegadeesh & Titman, 1993; 2001). As the model only has one proxy for risk, it leaves several factors such as company size and thus liquidity out of consideration. Additionally, the problems may also rise from the underlying assumptions; expecting investor rationality and the absence of transaction costs and taxes may very well be questioned. Lastly, the beta is obtained through a simple OLS-regression ran on past data and is thus not stationary through time: the asset's beta is ever-evolving. (Bodie et al., 2014.)

3.3.1 Fama-French Three-Factor Model

As the CAPM fails to explain several anomalies, such as the outperformance of small-cap and value stocks, Fama and French (1993) introduce a new model on explaining equity returns. The model includes two new variables concerning the size and price-to-book value, making the total variables three. The model is expressed as follows:

$$R_i - r_f = \propto_i + \beta_i(r_m - r_f) + \beta_{SMB}SMB + \beta_{HML}HML + \varepsilon_i \quad (19)$$

Where $\propto_i$ is a constant expected to not differ from zero if the model holds. As in CAPM, β_i is the exposure to the overall market return (r_m) and thus macroeconomic risk factors. β_{SMB} is the exposure to the return of a Small Minus Big portfolio (SMB) which is the return of a small-cap portfolio minus the return of a large-cap portfolio. While β_{HML} is the exposure to the return of a High Minus Low (HML) portfolio which is the return of a portfolio investing in high price-to-book stocks minus the return of a low price-to-book stock portfolio. ε_i is an error term with an expected mean of zero. (Bodie et al., 2014.)

In terms of explanatory power, the proposed three-factor model is an improvement over CAPM. Liquidity is indirectly included as a risk factor through the Small Minus Big variable. However, the model has its flaws as it still cannot explain majority of the variation related to investment behaviour and profitability (Novy-Marx, 2013; Titman, Wei & Xie, 2004). Additionally, the model still has trouble explaining the returns on momentum strategies (Jegadeesh & Titman, 1993). Due to this, Carhart (1997) proposes momentum factor to be added to the model, thus making the total number of variables four.

3.3.2 Fama-French Five & Six-Factor Models

Fama and French (2015) improve their earlier model by the inclusion of two new factors, making the total number of factors five. The inclusion of these factors is driven by Novy-Marx (2013) findings on the importance of profitability and Titman et al. (2004) findings on the negative relationship between abnormal capital investments and future expected returns. The two new factors aim to capture the variability caused by the profitability and investment behaviour; the model is expressed as follows:

$$R_i - r_f = \propto_i + \beta_i(r_m - r_f) + \ \beta_{SMB}SMB + \ \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA + \varepsilon_i \quad (20)$$

where β_{RMW} is the exposure to the return of a Robust Minus Weak (RMW) portfolio which is the difference between the returns of two diversified portfolios with robust (weak) profitability. β_{CMA} is the exposure to the return of a Conservative Minus Aggressive (CMA) portfolio which is again the difference between two diversified portfolios consisting out of stocks with conservative (aggressive) investment behaviour. The rest of the variables are as in the earlier three-factor model. (Fama & French, 2015.)

The five-factor model is a clear improvement over the earlier model as it explains between 71% and 94% of the variation in expected returns with the chosen factors. A momentum factor is still not included in this model, this is due to its correlation with some of the other factors as a momentum portfolio would more than likely include stocks already inside some of factor portfolios. (Fama & French, 2015.) This still causes the model problems in explaining the returns for momentum strategies (Grobys et al., 2018; Ruenzi & Weigert, 2018). However, fundamentally the model is not built for explaining the returns on momentum.

In their newer paper, Fama and French (2018) include momentum in the model as a sixth factor, resulting in an increased explanatory power for the model. The rest of the explanatory variables are again the same as earlier, making the final regression model:

$$R_i - r_f = \propto_i + \beta_i(r_m - r_f) + \ \beta_{SMB}SMB + \ \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA + \beta_{CMA}UMD + \varepsilon_i \ . \quad (21)$$

Here, UMD (Up Minus Down) is the return on a value weighted portfolio formed at time t-1. The return on this portfolio is the return of a portfolio containing stocks with the highest average returns (70th percentile) during a prior 12-month time period (t-12 to t-2) minus the return of a portfolio containing the bottom 30th return percentile.

To closely examine the strategy (portfolio) returns, the empirical part of this thesis applies the Fama-French three and six factor models. Even though the three-factor model poorly explains momentum returns, the regression is run to see whether the strategy (portfolio) exposures towards the three mutual risk factors change between the model regressions.

4 Commodity Futures

Commodities are real assets and thus differ greatly from the more traditional asset classes. Commodities can be distributed into two categories: investment commodities (mainly precious metals) and commodities used for consumption (e.g., industrial metals and agriculture products). Commodities do not produce any cashflows and thus an investor is rewarded solely by the potential price fluctuations which arise from the changes in the global supply and demand for the underlying commodity. Notably, the price fluctuations are subject to seasonality effects and are considered much more volatile when comparing to equities or bonds. (Gorton & Rouwenhorst, 2006.)

There are several available ways of investing in commodities. However, this thesis focuses on commodity futures as the attributes (high liquidity, low transaction costs, no short-selling restrictions) of commodity futures markets are optimal for implementing Momentum strategies (Miffre & Rallis, 2007).

Commodity futures are contracts that oblige the buyer to purchase a set quantity of the underlying commodity for a fixed price at a certain date in the future, the price is regarded as the future price. However, the contracts do not have to end in a physical delivery of the underlying, as the positions can be closed or rolled over before the set delivery date. Futures contracts are traded on exchanges, such as the Chicago Mercantile Exchange (CME). (Hull, 2015.)

The futures markets are forward looking. The futures price arises from the unbiased consensus expectations of the market participants about the spot price in the future. Naturally, the expectations are heavily influenced by the current spot price. Thus, the price fluctuations on futures prices are directly linked to the *unexpected* price fluctuations in the underlying asset. This characteristic makes futures contracts a great alternative to gain exposure to the price movement on various commodities. However, it should be underlined that the e*xpected* movements in the spot price are already incorporated in the consensus for the future price. (Gorton & Rouwenhorst, 2006.)

No capital changes hands at the inception of a futures contract. This raises inherent counterparty risks, which are mitigated with the usage of margin accounts. To limit credit risk, both parties are required to deposit a sum of capital into a margin account when entering a futures contract. This capital is used for daily settlements which reflect the investor's gain or loss on the position. However, the capital required for the initial margin is notably lower than the value of the entire underlying contract. Thus, investors acquire notable leverage when entering long or short positions in a futures contract. (Hull, 2015.)

The daily capital gain (loss) for an investor with a long (short) position in a futures contract is directly affected by the change in the current spot rate as it directly affects the future expectation for the spot rate. The capital gain (loss) is the difference between the set contract price (K) and the expected future spot rate (S_t):

$$R_{Long} = S_t - K \tag{22}$$

$$R_{Short} = K - S_t \tag{23}$$

The buyer of the contract expects the future price to be above the set contract price whereas the seller expects it to below it; both sides bear the risk of unexpected spot price movements. The returns on futures positions are further illustrated in Figure 3. (Hull, 2015; Gorton & Rouwenhorst, 2006.)

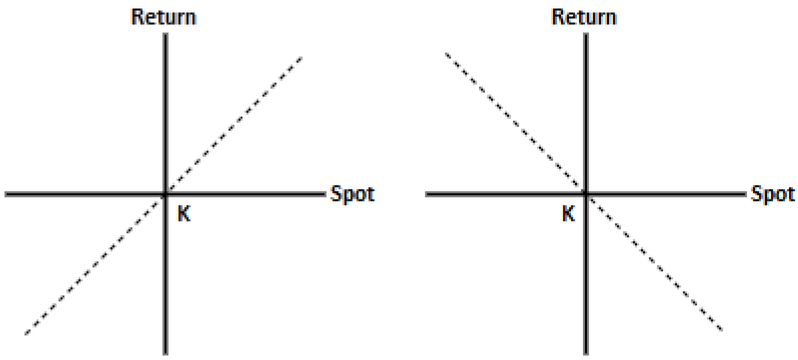

Figure 3. Long and short futures positions (Hull, 2015)

As the expected spot price changes are already incorporated in the consensus future price (i.e., the set contract price, K), an investor can only profit upon the realization of the unexpected movements of the spot prices. Due to the latter, futures prices include a time-varying risk premium, which is the difference between the current and expected future price (Gorton & Rouwenhorst, 2006):

$$Risk\ premium = E[F_T] - F_0 \tag{24}$$

If the current futures price (F_0) is below (above) the expected futures price ($E[F_T]$) the investor holding the long (short) position will earn a positive risk premium.

The risk premium on futures prices is explained by Keynes' (1930) theory of *normal backwardation* which asserts that on aggregate the holders of long positions in futures contracts are awarded with positive risk premiums. The theory is based in a world where there are two types of agents: speculators and hedgers. The hedgers seek to nullify the price risk of their production, the speculators provide them the futures to do so; simultaneously making a bet on the expected future price. In aggregate the speculators will not make bets with negative expected values. Therefore, to provide a margin of safety the futures price is set below the real expected future price, forming a positive risk premium. Uncertainty about the future price increases as the maturity of the contract draws further. Thus, the risk premium is at its highest point at the inception of the contract –

as time passes the risk premium starts gradually decreasing; making the futures price approach the real expected future price as the contract nears maturity. The concept of future prices rising during the lifetime of the contract is called *normal backwardation*. Such behaviour of prices would lead to substantial returns from holding long positions in far maturity contracts and rolling the position over as the contracts near maturity. These efforts result in the investor gaining a continuous positive risk premium (return), assuming the futures markets are trading in *backwardation*. (Gorton & Rouwenhorst, 2006; Miffre & Rallis, 2007.)

The opposite, futures price being above the spot price and then decreasing through time is called *contango*. Contango occurs when there is substantial hedging pressure from the consumers. This results in a massive influx of opened long positions in futures contracts, causing the speculators to do the exact opposite to the earlier situation. If markets are trading in contango, an investor will lose money if they are holding long positions in the futures contracts. However, an investor holding short positions in far maturity contracts (and rolling them over) will on average turn a profit. (Gorton & Rouwenhorst, 2006; Ilmanen, 2011.) Both market states; contango and backwardation are illustrated in Figure 4 below.

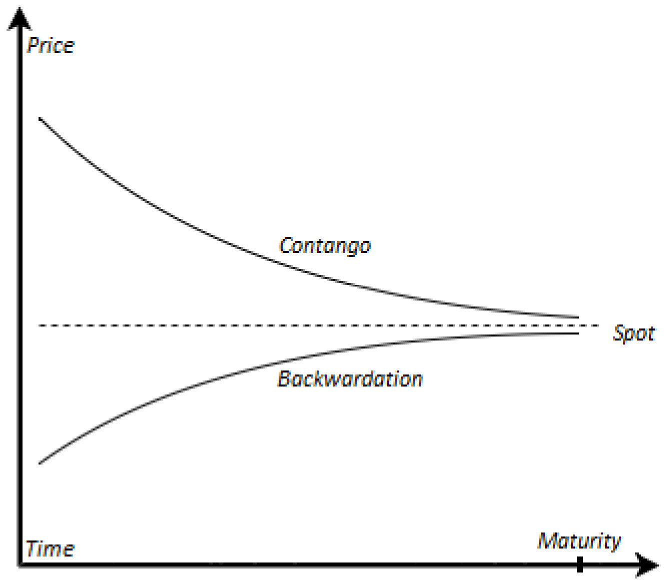

Figure 4. Contango and backwardation

Considering the earlier discussed; the total return on a commodity futures position can be decomposed into three components:

$$Total\ return = Change\ in\ Spot + Interest + Roll\ return \tag{25}$$

A small part of the total return is the interest gained on the collateral deposited in the margin account, which usually is the risk-free rate of return. Naturally, a part of the return is caused by the *unexpected* changes in the spot price. As briefly discussed above, the roll return can arise from holding long or short positions in futures contracts for extended periods of time. As the contract nears expiry, to avoid taking delivery of the underlying (and to keep their long exposure on the underlying) an investor must roll their position over to a new contract with a further expiry date. The roll return is positive if the price of the new contract with further expiry is below that of the sold contract, i.e., the markets are trading in *backwardation*. The exact opposite is true if the markets are in *contango*. Historically, the roll returns are a key driver for the total returns across different commodity futures. The importance of the roll yield is shown in Figure 5 which illustrates the return on two equal weighted commodity portfolios. The total return portfolio captures the roll return by rebalancing and rolling over the futures positions monthly. The spot portfolio shows the returns from investing in the same commodities straight through the spot market, thus missing out on the roll returns. (Levine, Ooi, Richardson & Sasseville, 2018.)

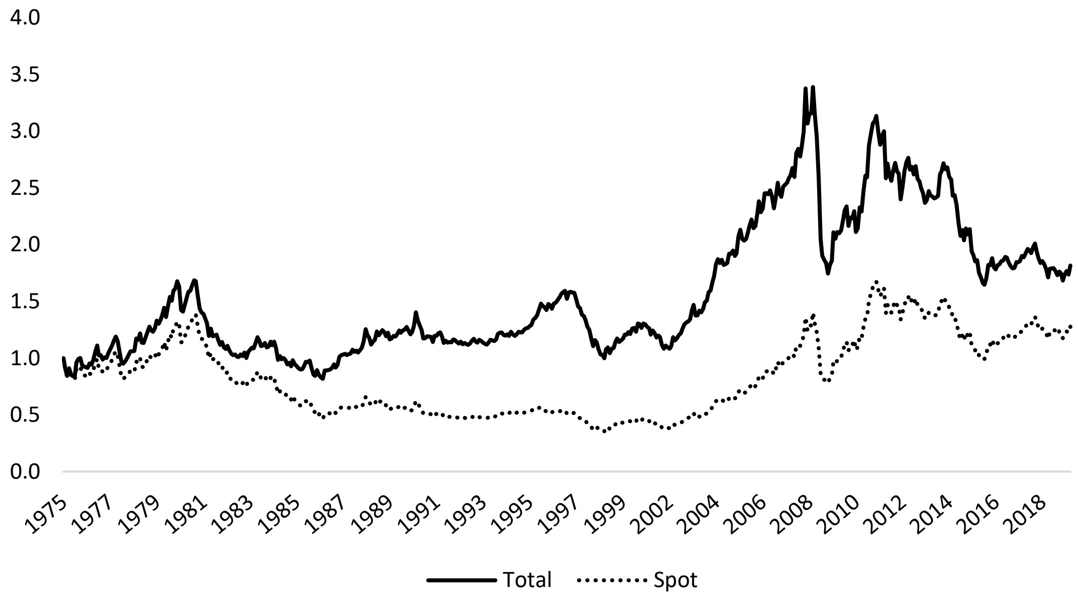

Figure 5. Spot vs. futures return (Levine et al., 2018).

4.1.1 Pricing Commodity Futures

Apart from interest paid on the collateral deposited in the margin account, commodity futures do not generate cashflows for the investor. Thus, regular cashflow models are of no use for determining the price of commodity futures. The pricing of commodity futures depends on the commodity at hand. Futures on investment commodities, such as gold are priced differently when compared to the futures on commodities used for industrial production, such as copper or soy. (Hull, 2015.)

As commodities introduce storage costs to the holder, the present futures price for an investment commodity can be expressed as follows:

$$F_0 = S_0 e^{(r+u)T} \tag{26}$$

where S_0 is the current spot price of the underlying, r is the current risk-free return p.a. and u is the storage cost p.a. as a proportion to the current spot price. T is the length of the contract in years. (Hull, 2015) The two components (r and u) may be considered a cost of carry for the counterparty holding the asset. Naturally, if the costs of storage or the opportunity cost (the risk-free rate) increase, the counterparty must be compensated, thus resulting in an increased futures price. The markets will contain arbitrage opportunities if the equality does not hold. If, for example, the current futures price (F_0) is exceeds the price in Equation 26, an arbitrageur will sell a futures contract, take a loan at the risk-free rate to pay for the purchase and storage costs of the underlying and hold this position until the expiration of the contract. Upon expiry, the arbitrageur will sell the underlying at the set contract price and repay the loan, collecting a return exceeding the risk-free rate. (Hull, 2015).

Consumption commodities may be used for production at any point in time, thus having such commodities available for refining provides the holder with a convenience yield. The convenience yield is directly linked to the current and future expected availability of the underlying commodity. If global inventories are running low, the convenience of having the underlying is higher than it would be in the opposite situation. (Hull, 2015.) When convenience yield is introduced, the futures price can be expressed as follows:

$$F_0 = S_0 e^{(r+u-cy)T} \tag{27}$$

a positive convenience yield (cy) decreases the futures price. During extreme events, the convenience yield may offset the storage costs and risk-free return, making the futures price be quoted below its current spot price. (Hull, 2015.)

Gorton, Hayashi and Rouwenhoorst (2013) find that the convenience yield has a decreasing non-linear relationship to the level of physical inventories. Thus, when inventories are low, the convenience yield is high and vice-versa. Furthermore, as the relationship is non-linear, the effect is amplified at the extremes (i.e., when inventories are *really low* convenience yield is *really high*, and vice-versa). Considering inventories' link to convenience yield and equation (27) above, it comes without saying that the inventory levels have a major impact on the market prices for futures contracts; rapidly decreasing (increasing) inventory levels will likely lead to the market trading in contango (backwardation).

The behaviour of inventory levels is different between various commodities based on their individual characteristics. For example, the inventory levels for many agricultural commodities dwindle just before the new crop is harvested. As the new crop is harvested, the inventory levels skyrocket and start slowly decreasing as the growth cycle for the next crop begins. Contrary to agricultural commodities, commodities such as industrial metals can be produced thorough the year, and thus the inventory level remains relatively stable. However, what is mutual for all commodities is that the inventory levels are slow to adjust to shocks. For example, demand shocks that cause inventory levels to decrease tend to remain in place for longer periods of time. (Gorton et al., 2013.) Considering the link between inventories and the futures prices, the slow adjustments should create opportunities for trend following trading strategies, such as momentum.

4.1.2 Commodity Futures: Risk, Return and Correlation

To further motivate the construction of equity-commodity futures momentum portfolios, this section reviews some of the literature examining the relationship between long-only positions commodity futures and equities.

The return on commodity futures and their correlation to other financial assets have developed through time. One of the earlier studies by Ankrim and Hensel (1993) finds the commodity futures market (the GSCI) outperforming the S&P500 by a large margin during a 19-year sampling period (1972-1990). During the period, the average yearly return on the GSCI was 17%, outperforming the S&P500 by 5.3%. Interestingly, the volatility did not seem to be a good explanator of the excess returns, as it was just 3.2% above the volatility of S&P500 (19.5 vs. 16.3). However, majority of the difference is explained by the economic crises that occurred in the 1970s. During the inflationary 70s, the commodities earned on average 21.6% p.a., whereas the S&P500 earned 8.8% p.a. The tables turned as the equity markets began rallying for the entirety of the 1980s, earning 14.4% p.a. compared to the commodities 12.8% p.a. (Ankrim & Hensel, 1993.)

These findings are further supported by those of Jensen, Johnson and Mercer (2000) who find the GSCI to continue its positive performance thorough the 1990s. However, this thesis expands the previous one by reviewing the performance of the asset classes during times of expansive and restrictive monetary policy. The results are robust: during expansive policy (times of low inflation) stocks significantly outperform commodities (1.735% per month vs. 0.335%). As expected, during restrictive monetary policy (during times of heightened inflation) the roles reverse; commodities outperform equities by a substantial amount (1.993% vs. 0.357% per month). (Jensen et al., 2000.) These findings support the assertion that commodities operate as a hedge against inflation. This is also supported by the findings of Gorton and Rouwenhorst (2005) who find the correlation between the GSCI and inflation to be 0.29 whereas the correlation for S&P500 and inflation is -0.10.

After the early 2000s, the returns on commodity futures have diminished greatly. During a 10-year sampling period (2005-2014) Bhardwaj et al. (2015) find the average yearly return on the GSCI to be 5.09%, thus, losing substantially to the S&P500. However, this time was accompanied with extremely expansive monetary policy such as the first three quantitative easing programs. Thus, based on the findings of Jensen et al. (2000) one should expect commodities to underperform equities during such times.

As proven earlier in Chapter 2.1., the correlations between asset classes are of paramount importance when improving a portfolio's risk to return ratio. The correlation between the commodity futures markets and the equity markets is often found to be near-zero or negative. Ankrim and Hensel (1993) find the GSCI to pose a correlation of -0.06 to the S&P500 during their entire sampling period (1972-1990). Such correlation was also present during the 1990s, where the GSCI posed a correlation of -0.04 towards the

S&P500 (Jensen et al. 2000). Gorton and Rouwenhorst (2005) find the correlation to fluctuate with the measurement period. During a sampling period of 45 years (1959-2004), the correlation between GSCI and S&P500 decreases from 0.05 (monthly) to negative 0.10 (yearly) and all the way to -0.42, when computed with 5-year returns.

After the early 2000s, the correlation between commodities and equities has increased tremendously reaching 0.60 during the sampling period from 2005 to 2014 (Bhardwaj et al., 2015). Bhardwaj et al. (2015) argue that the increased correlation may be caused by the *"financialization"* of the commodity futures markets. The term is used to describe the substantially increased investor presence in the markets. The presence has increased especially through the various index funds following the commodity futures markets. This causes the prices of individual commodities not to be set by the fluctuations in the supply and demand equilibrium anymore, but rather by multiple other financial factors, such as investor sentiment and risk tolerance. This development has also led to the higher correlations within the futures markets. (Bhardwaj et al., 2015; Tang & Xiong, 2012.)

All the main findings made on the risk, returns and correlations on commodity futures are illustrated in Table 2.

Table 2. Commodity futures: risk, return and correlations.

	Period	***μ p.a. (%)***	***σ p.a. (%)***	***ρ to Equity***
Ankrim & Hensel (1993)	1972 - 1990	*17.00*	*19.50*	-0.03
Jensen et al. (2000)	1973 - 1997	*12.58*	*18.16*	-0.04
Gorton & Rouwenhorst (2006)	1959 - 2004	*11.46*	*12.02*	-0.10
Bhardwaj et al. (2015)	2005 - 2014	*5.09*	*15.23*	0.60

5 Momentum Strategies

The purpose of this chapter is to familiarize the reader to the momentum anomaly, which is present globally and in several different asset classes. The first part of the chapter is devoted for understanding the principles of momentum strategies. Afterwards, literature concerning the momentum effect in both equity and commodity futures markets, is reviewed. The latter part of the chapter is spent on examining momentum crashes and on ways of improving the performance of momentum strategies. The chapter finishes with an overview on the most regarded explanations on the momentum anomaly.

5.1 **Principles**

The underlying idea behind momentum strategies lies within the nature of asset price movements. In aggregate, as asset prices are rising, they have a sticky tendency of continuing the upward drifting trend. This finding is also true with downwards moving prices, past losers are often found continuing the downward trend (see e.g., DeBondt & Thaler, 1985; Frazzini, 2006; Jegadeesh & Titman, 1993).

The implementation of a momentum strategies can be divided into three steps. Figure 6 illustrates a simple 12-1-1 momentum strategy run for three iterations. The strategy is simplified into a K-L-M format. The longest period of 12 months (from t = -12 to t = -1), K, is a cumulation period in which the assets cumulative returns during the 12-month period are gathered and ranked from highest to lowest.

The L indicates the length of a skipping period, which often varies between 0 and 7 months depending on the strategy at hand. In the literature covering momentum, the skipping of the most recent month (L = 1) is considered a standard. The single skipping month aims avoid one-month price reversals often found in the equity markets. The reversals are argued to originate from liquidity and market microstructure issues. However, these reversal issues are less relevant in other asset classes (e.g., commodity futures or fixed income). (Asness et al. 2015.)

After the cumulation, ranking and skipping processes, an investment portfolio is formed generally from the top and bottom decile (or quintile) assets. The portfolio holds long positions in the assets which posted the highest cumulative returns during the 12-month period and shorts the worst performed assets. Therefore, the constructed portfolio is betting on the continuation of the past price trends. In majority of the literature all long and short positions are equally weighted, making the long and short positions both equal 50% of the entire portfolio. The positions are then held for a month and after the initial holding period (M) the process is run for a second iteration. Now the cumulative returns are gathered from a new 12-month period ranging from t = -11 to t = 0 on the original timeline. In this example, the process continues for three iterations always moving forward by one month. (Jegadeesh & Titman, 1993.)

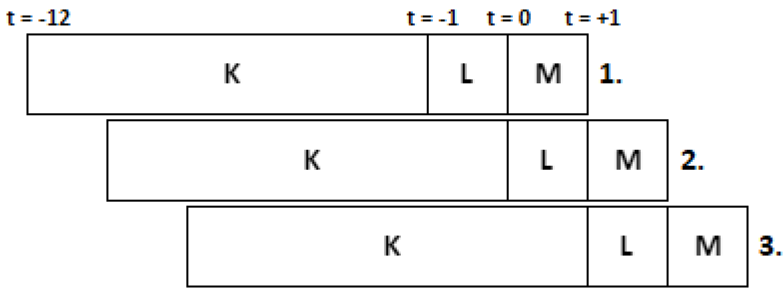

Figure 6. Three-period K-L-M strategy

The so-called 12-1-1 strategy is but one example of the wide variety of strategies examined in the literature. Several strategies with varying periods pose significant positive alphas (=returns, which cannot be explained by the equity pricing models). However, in the recent literature strategies basing the ranking process on a 12-month period are found to significantly outperform strategies using a shorter ranking period, such as the 6-1-1 strategy. Additionally, some strategies use a 7-month skipping period with great success, suggesting that the momentum effect may be more of an echo of past performance than a continuation of the most recent trend. (Novy-Marx, 2012; Goyal & Wahal, 2015.) Generally, the holding period (M) remains as a single month, as the momentum effect diminishes over longer periods of time (Jegadeesh & Titman, 1993; 2001; Asness et al. 2013; 2015).

Overall, the momentum strategies are zero-cost as the capital required for the long positions is raised through the simultaneously opened short positions. Thus, the pay-off from such strategy can be illustrated as follows:

$$R_{WML} = R_W - R_L \tag{28}$$

Where R_W is the return from the long positions (past winners) and R_L is the return on the opened short positions (past losers).

5.2 **Equity Momentum**

The first paper covering momentum is considered the 1993 paper by Jegadeesh and Titman (1993). In the paper several momentum trading strategies are under examination, all of which are executed over a 25-year period (1965-1989). These strategies are executed with a cumulation (K) and holding (M) periods ranging between 1 to 4 quarters (3 to 12 months). The winner and loser portfolios are formed from the top (bottom) return deciles. To achieve a zero-cost strategy, all portfolios are equally weighted; both the long- and short legs are exactly 50% of the entire portfolio. Additionally, to avoid price pressure and lagged reaction effects, half of the momentum portfolios use a single skipping week (L) between the cumulation and holding periods. (Jegadeesh & Titman, 1993.)

The results are striking; the winner portfolios consistently outperformed the loser portfolios by a large margin. Only one out of the 32 loser portfolios (3-0-3) provides a statistically significant return of 1.08% per month. In contrast, all the winner portfolios provide statistically significant returns. These average monthly returns vary between 1.40% and 1.92%. Naturally, the results above make the returns extremely robust for the zero-cost momentum portfolios. All but one of the 32 long-short portfolios pose statistically significant positive average monthly returns varying between 0.58% and 1.49%, which is a direct violation of the earlier discussed weak form EMH. The only insignificant return is provided by the portfolio investing with a 3-0-3 strategy, which is caused by the positive return on the short leg. (Jegadeesh & Titman, 1993.)

The abnormal returns of the zero-cost portfolios cannot be attributed to their systemic risk exposures, nor the exposures to the three Fama-French factors. Additionally, Jegadessh and Titman (1993) conclude the returns cannot be attributed to lead-lag effects which would result from slow stock price reactions to news. However, Jegadeesh and Titman (1993) argue that the abnormal returns may originate from investor overreaction and its effect on return persistence.

The persistence of a 6-0-6 momentum strategy is replicated in the later paper of Jegadeesh and Titman (2001), in which the strategy is implemented over an eight year longer sample period than before (1965-1998). Additionally, the study also reviews the performance of a 6-0-6 momentum portfolio investing only in large or small cap stocks (Jegadeesh & Titman, 2001).

The strategy works on both, small and large cap stocks. However, the returns on small cap momentum are superior to those of its large cap counterpart (1.42% monthly vs. 1.03% over the entire sampling period). The notable difference may be explained by the different levels of liquidity between small and large cap stocks, thus implying that momentum may work better in an illiquid environment (Jegadeesh & Titman, 2001). The later findings of Butt and Virk (2017) on momentum and liquidity support this assertion.

As the results seem robust for the U.S. markets, a natural continuation is to study their performance in an international setting. Rouwenhorst (1998) examines the performance of a momentum strategy using an investment universe of 2,190 stocks in 12 European countries within a period of 18 years (1978 – 1995). The momentum strategies under examination are the same as in the original paper of Jegadeesh and Titman (1993).

As earlier, the returns on the zero-cost portfolios are positive and statistically significant. In aggregate, the zero-cost strategies earned an average monthly return ranging between 0.64% and 1.35%. Again, the returns cannot be explained by the regular CAPM, as the strategies are by construction close to being market neutral meaning their return should equal the risk-free rate. The performance cannot be explained by the three-factor model either, the zero-cost portfolios pose significant positive alphas over the entire sampling period. (Rouwenhorst, 1998.) These findings are like those made in the U.S. markets by Jegadeesh and Titman (1993; 2001), which implies momentum is persistent in the developed markets. Interestingly, the returns on the European momentum portfolios are significantly correlated to their U.S. counterparts, suggesting that momentum might be a cross-market factor (Rouwenhorst, 1998). Additionally, Rouwenhorst (1998) finds the strategies with a skipping a month between the cumulation and holding periods outperforming those without. Again, the strategy returns diminish quickly as holding periods grow longer, suggesting that the momentum effect diminishes over time. Both findings support those of Jegadeesh and Titman (1993; 2001).

In addition to the developed markets, momentum strategies pose significant returns even in the emerging markets. Rouwenhorst (1999) examines the performance of similar momentum strategies using price data from 20 emerging stock markets over a 15-year period (1982-1997). 17 out of the 20-country specific zero-cost momentum portfolios pose a positive return. (Rouwenhorst, 1999.)

The emerging market momentum portfolios pose a significantly lower monthly returns to their developed market counterparts (0.39% vs. 1%). However, there is a major difference in the portfolio formation between the markets. Due to lack of investable securities, the emerging market portfolios contain the 30% deciles instead of the regular 10% deciles. This broadens the emerging market portfolios significantly: the top 30% may not be the absolute “winners” anymore, but rather equities which posed an adequate return. (Rouwenhorst, 1999.) This suggests that momentum returns may disappear if the chosen securities do not reside in the opposite past return extremes. In turn, this could cause problems to the prevalence of robust returns in commodity futures momentum strategies, as the total number of investable commodity futures is often under 30.

All findings discussed above are further supported by those of Asness, Ilmanen, Israel and Moskowitz (2015), who find robust evidence on the performance of a 12-1-1 momentum strategy within a broad sample that amounts to 90% of the global equity markets’ market capitalization. The sample data is collected from a period of 24-years (1990-2013); thus, it provides a thorough analysis on the performance of momentum strategies in the modern, digitalized world of investing (Asness et al., 2015).

In the studies discussed, measuring the performance in the past 12 to 6-months and skipping the most recent month is a staple. This approach assumes that the momentum effect arises from the recent performance (short-term autocorrelation in asset returns). However, Novy-Marx (2012) suggests that momentum is more of an echo than a continuation of recent trends, meaning that the performance further in the past predicts the future returns better than the most recent performance. Figure 7 illustrates the findings on returns based on past performance percentiles of two different cumulation periods. The dashed line presents the behaviour of the percentiles based on the ranking made during a recent 6-month period (i.e., the K of a 6-1-1 strategy). The solid line however uses a 6-month period based further in the past, presenting the cumulation period of a 12-7-1 strategy. The notably steeper solid line clearly shows a stronger relationship between further past and near-future expected returns, thus supporting the hypothesis of momentum being more of an echo (Novy-Marz, 2012). The slope of the curve in panel B also suggests that majority of the profits for equal-weight momentum strategies come from the winner portfolio, supporting the early findings of Jegadeesh and Titman (1993; 2001) along with the findings of Rouwenhorst (1998).

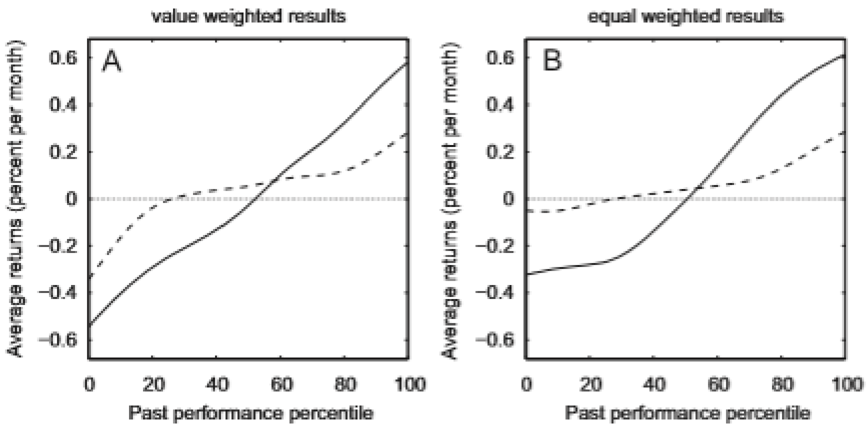

Figure 7. 12-7-1 vs. 6-1-1 (Novy-Marx, 2012)

During a sampling period of 83 years (1927-2010), the proposed 12-7-1 strategy clearly outperforms the 6-1-1 strategy, especially when correcting for risk with the Fama-French factors. On average the 12-7-1 strategy poses a positive significant alpha of 1.20% per month whereas its 6-1-1 counterpart poses an average significant alpha of 0.67% per month. The difference (0.54%) in the two strategies' returns is statistically significant, again supporting the earlier hypothesis. The findings remain the same for several asset classes and markets, such as international equity indices, commodity futures and currencies. (Novy-Marx, 2012.)

Grobys (2016) finds supportive evidence on the performance of the 12-7-1 strategy when implemented on the German DAX 30 equity index. However, in contrast to Novy-Marx (2012), the strategy is outperformed by the regular 12-1-1 and 6-1-1 strategies in this asset universe (Grobys, 2016). Furthermore, the work of Novy-Marx (2012) is directly critiqued by Goyal and Wahal (2015) who find no robust evidence on the outperformance of the 12-7-1 strategy in global developed nor emerging equity markets. Thus, they assert that the "echo" seems to only appear in the U.S. markets (Goyal & Wahal, 2015).

5.2.1 Momentum Crashes

As the three and five-factor models failed to explain the returns on momentum strategies, there must clearly be a hidden component to the risk which explains the substantial excess returns (Jegadeesh & Titman, 1993 & 2001; Rouwenhorst, 1999). The analogy *"collecting dimes in front of a steamroller"* is depictive of the situation at hand when implementing unhedged momentum strategies for long periods of time. The distribution of the returns on momentum strategies is negatively skewed, thus suggesting an increased likelihood of extreme negative events. Occasionally equity momentum strategies experience severe crashes like those experienced in currency carry-trades. These crashes occur during and after states of panic, mainly following major market meltdowns and times of heightened market volatility (Daniel & Moskowitz, 2016). Additionally, momentum strategies possess inferior performance during recessions. Grobys (2014) finds recessions to reduce the monthly performance of a momentum strategy by more than 2.2%, making the average returns negative.

As discussed earlier, during normal market activity, equity momentum strategies are close to being market neutral (Jegadeesh & Titman, 1993; 2001). However, market exposure significantly fluctuates when markets experience heightened uncertainty. During severe bear markets, momentum strategies pose a -0.70 beta towards the market as it is spiralling downwards, thus continuing the impressive gains on the way down (Daniel & Moskowitz, 2016). The positive performance during market downturns may be explained by the market liquidity. Increasing liquidity affects equity prices positively (Amihud, 2002). During market downturns liquidity starts to evaporate which starts a flight to liquidity phenomena, resulting in investors flocking into more liquid stocks. In general, the past winners are far more liquid than the past losers. Because of the latter, the value of the loser portfolio falls more than the value of the winner portfolio, resulting in a positive overall return and thus, a negative beta to the overall market. (Butt & Virk, 2017.)

However, the problem arises as the market reverses and starts recovering. During post-bear market reversals, the momentum exposure to the overall market is -1.51, making momentum crashes occur when the overall market returns are high (Daniel & Moskowitz, 2016). These crashes can be attributed to the behaviour of the short leg (the loser portfolio). During market reversals, the past 12-month winner portfolio poses significantly lower returns than the overall market. However, after the reversal, the short leg experiences significantly higher returns than the overall market, resulting in significant losses from the short positions. (Daniel & Moskowitz, 2016.)

The behaviour of the short leg makes it essentially a written call option during bear markets. The maximum upside on the shorted stocks is limited to 100% which presents the premium received on the option. However, the potential downside on the stocks is substantial as during bear markets, they are more than likely priced for bankruptcy. If a bankruptcy does not occur, the rebound on these shorted stocks is violent. During bear markets momentum returns decrease while the overall market variance increases. This clearly supports the notion of the option-like behaviour of the short leg, as rising uncertainty increases option prices. (Daniel & Moskowitz, 2016.) Another explanation for the higher returns on the loser portfolio may also be the sharply increasing market liquidity, which inverses the effect that occurred during the downturn (Butt & Virk, 2017).

Overall, this combination causes the zero-cost strategy to crash within a short period of time, wiping out majority of the invested capital in the worst cases. Table 5 presents the ten worst monthly returns for a momentum strategy investing in U.S. equities with respective to the underlying market. The rightmost column tracks the past 2-year returns on the underlying market. Apart from 2001, all momentum crashes followed a severe bear market. (Daniel & Moskowitz, 2016.)

Table 3. Momentum crashes (Daniel & Moskowitz, 2016)

Rank	Month	μ WML (%)	μ Mkt (%)	μ Mkt, past 2 years (%)
1	08 / 1932	-74.36	36.49	-67.77
2	07 / 1932	-60.98	33.63	-74.91
3	01 / 2001	-49.19	3.66	10.74
4	04 / 2009	-45.52	10.2	-40.62
5	09 / 1939	-43.83	16.97	-21.46
6	04 / 1933	-41.14	38.14	-59.00
7	03 / 2009	-42.28	8.97	-44.9
8	11 / 2002	-37.04	6.08	-36.23
9	06 / 1938	-33.36	23.72	-27.83
10	08 / 2009	-30.54	3.22	-27.33

The literature clearly suggests that momentum strategies contain a severe crash risk. Following this, one can argue that the abnormal returns from the strategies should then be corrected for such risk. Ruenzi and Weigert (2018) amplify the Fama-French three and five-factor models by including a fourth (sixth) variable. The variable is the return of an investment strategy that is long on equities with high crash sensitivity and short on equities with low crash sensitivity. The rationale is that investors dislike assets with high sensitivity to crashes, thus increasing the risk premium on them – resulting in higher expected returns (Kelly & Jiang, 2014). The equities included in the loser portfolio possess higher negative skewness, thus increasing risk premia and the probability of a price reversal if the skewness starts normalizing (Ruenzi & Weigert, 2018).

As seen earlier, when first correcting for the Fama-French three-factors, the momentum strategy poses a significant positive alpha (11.9%) over a 50-year sampling period (1963-2012). The alpha remains positive and significant (13.2%) even when correcting for the five factors. However, after controlling for the new source of risk, both alphas reduce significantly (to 1.8% and 2.9%) in addition to becoming indistinguishable from zero. Additionally, upon the inclusion of the fourth (sixth) variable, the R-squared nearly doubles for both models (from 0.10 to 0.18). (Ruenzi & Weigert, 2018.)

The findings on momentum crashes suggest that majority of the previously unexplained abnormal returns may just be an adequate compensation for the exposure to crash risk.

5.3 Commodity Futures Momentum

As the momentum effect is persistent through time within the equity markets, a relevant question is whether the effect is displayed in other markets. Miffre and Rallis (2007) test whether commodity futures prices show presence of short-term price momentum. This is done by examining the profitability of 56 different momentum and contrarian strategies. Contrarian strategies can be considered an opposite to regular momentum strategies; they short the winners and go long on the losers. In contrast to momentum, these contrarian strategies bet on the asset prices reversing to a long-term mean, which is a characteristic identified within the equity markets. (Miffre & Rallis, 2007; De Bont & Thaler, 1985.)

The strategies are executed in an asset universe consisting out of 31 different commodity futures over a 25-year time horizon (1979-2004). The return series for the futures are formed by continuously rolling over a position between the two nearest maturity contracts. As discussed in Chapter 4, this captures the possible positive (negative) roll return depending on whether the contracts are trading in backwardation or contango. The implementation of the momentum strategies differs slightly from the equity markets. Due to the low number of investable securities, the top and bottom quintiles (20%s) are used instead of the more regularly used deciles. As often in equity momentum, the contracts are equally weighted. (Miffre & Rallis, 2007.)

Over the entire sampling period, a long-only portfolio investing in commodity futures would have on average lost 2.64% p.a. Additionally, the contrarian strategies also consistently lost capital (Miffre & Rallis, 2007). The results for the different momentum strategies are depicted in Table 3 below, where the columns represent the holding periods (M) and rows the different ranking periods (K). In aggregate, the returns on the momentum strategies are positive and statistically significant. This evidence suggests that commodity futures prices may display similar price momentum that is present within the equity markets. The highest average returns are obtained from the 3-1-1 and 12-1-1 strategies, both of which are also found to be among the most profitable strategies within the equity markets. (Miffre & Rallis, 2007.) Similar to the equity markets, momentum returns are found to be short-lived and quickly deteriorates as the holding period grows longer.

Table 4. Commodity futures momentum (Miffre & Rallis, 2007)

		M = 1	**M = 3**	**M = 6**	**M = 12**
K = 1	µ p.a. (%)	10.87	8.14	7.65	5.27
	t-stat	(2.13)	(2.58)	(3.35)	(3.2)
	σ p.a. (%)	25.74	15.93	11.45	8.2
	Sharpe	**0.42**	**0.51**	**0.67**	**0.64**
K = 3	µ p.a. (%)	13.8	10.46	7.64	5.47
	t-stat	(2.79)	(2.47)	(2.34)	(2.23)
	σ p.a. (%)	24.94	21.3	16.35	12.14
	Sharpe	**0.55**	**0.49**	**0.47**	**0.45**
K = 6	µ p.a. (%)	11.88	8.68	9.05	2.05
	t-stat	(2.37)	(1.93)	(2.3)	(0.65)
	σ p.a. (%)	25.15	22.52	19.61	15.55
	Sharpe	**0.47**	**0.39**	**0.46**	**0.13**
K = 12	µ p.a. (%)	14.60	8.43	0.96	-3.00
	t-stat	(2.84)	(1.86)	(0.23)	(0.82)
	σ p.a. (%)	25.57	22.36	20.72	17.88
	Sharpe	**0.57**	**0.38**	**0.05**	**-0.17**

All statistically significant returns are again adjusted for factor risk and tested whether they pose an alpha significantly differing from zero. However, as the earlier used three-factor model is designed with equities in mind, a new model is developed. The new model aims to explain the commodity futures momentum returns based on the movements of the S&P500, Goldman Sachs Commodity Index (GSCI) and Datastream Government Bond indices. Table 4 below illustrates the alphas and the Beta exposures to the GSCI and S&P500 for each of the strategies under examination, the bond index is not presented as all exposures towards it are insignificant. Much like the equity momentum strategies, the 12-1-1 strategy poses the highest alpha of 16.04% p.a. These findings are especially interesting as the commodity futures markets pose immense liquidity, which is often found to hinder momentum returns (Miffre & Rallis, 2007; Butt & Virk, 2017). On average, the beta exposures to the commodity market index (GSCI) are much higher than those of the equity momentum strategies, which are found nearing zero. The beta exposures to the S&P500 are nearing zero and insignificant on a 10% level (Miffre & Rallis, 2007). Notably, the diversification ability of the commodity futures momentum strategy is similar to long only positions in commodity futures highlighted in Chapter 4.1.2 (insignificant, near zero beta exposure towards S&P500 likely rises from a low correlation between the two time-series). Thus, the presented momentum strategies would likely enhance the risk-return characteristics of a portfolio holding only a long position in the S&P500.

Table 5. Alphas and beta exposures (Miffre & Rallis, 2007)

		M = 1	M = 3	M = 6	M = 12
K = 1	**Alpha (%)**	**10.87**	**8.89**	**8.02**	**5.77**
		(2.11)	(2.79)	(3.48)	(3.49)
	GSCI	-0.181	0.103	0.068	0.657
		(0.21)	(1.94)	(1.76)	(2.37)
	Mkt	-0.082	-0.053	-0.001	-0.028
		(0.83)	(0.88)	(0.02)	(0.89)
K = 3	**Alpha (%)**	**15.00**	**11.44**	**8.28**	**6.31**
		(3.02)	(2.71)	(2.53)	(2.58)
	GSCI	0.218	0.216	0.154	0.115
		(2.64)	(3.08)	(2.82)	(2.77)
	Mkt	-0.066	0.009	0.027	-0.058
		(0.72)	(0.11)	(0.43)	(1.24)
K = 6	**Alpha (%)**	**12.94**	**9.48**	**9.54**	
		(2.56)	(2.09)	(2.39)	
	GSCI	0.154	0.173	0.098	
		(1.83)	(2.28)	(1.47)	
	Mkt	-0.067	0.016	-0.017	
		(0.69)	(0.19)	(0.22)	
K = 12	**Alpha (%)**	**16.04**	**9.78**		
		(3.11)	(2.16)		
	GSCI	0.206	0.182		
		(2.38)	(2.38)		
	Mkt	-0.118	0.108		
		(1.22)	(1.24)		

Miffre and Rallis (2007) find that the winner (loser) portfolio often has positions in contracts trading in backwardation (contango). As discussed in Chapter 4.1., holding long (short) positions in contracts trading in backwardation (contango) returns the investor with a positive risk premium. Thus, the momentum strategy managed to capture a significant portion of the risk premiums, which may be the underlying reason behind the high annualized returns and strategy alphas.

The findings of Miffre and Rallis (2007) are further supported by the findings of Gorton et al. (2013) in addition to Asness et al. (2013) who find a 12-1-1 commodity futures momentum strategy to pose significant average return of 13.1% p.a. over a sampling period of 40 years. The returns are made with an average annual volatility of 23.4% making the Sharpe ratio 0.53. After correcting for Fama-French three factor exposures, the strategy still poses a significant positive alpha of 11.4%. This strongly supports the hypothesis that commodity futures prices pose the same momentum characteristics found in the global equity markets (Asness et al., 2013). Additionally, the persistence of momentum is visible even on an index level. A momentum strategy going long or short depending whether the previous year's S&P GSCI return was above or below zero is found to pose great success during 1982-2004 (Erb & Harvey, 2006).

While studying the correlations between the different momentum strategies, the returns on the commodity futures momentum pose a correlation of 0.20 towards the regular equity momentum. This could result in notable diversification benefits, even though the realized volatility of the commodity futures momentum is found nearly double that of its equity counterpart (23.4% vs. 12.0%). (Asness et al., 2013.)

The earlier studies were solely implemented on return series built from rolling over the two nearest maturity futures contracts. As mentioned before, this method captures the positive (negative) risk premium depending on whether the contract is trading in backwardation or contango. Chaves and Viswanathan (2016) implement momentum strategies on commodity spot returns. In contrast to the earlier findings, the contrarian strategies are successful when implemented on the spot prices; the spot prices present notable mean reversions over different time horizons. Such finding destroys the possible momentum returns as the contrarian strategies are effectively being shorted in the momentum strategies. Thus, there is no evidence of momentum being present in the commodity spot prices. (Chaves & Viswanathan, 2016.)

Based on the findings, Chaves and Viswanathan (2016) argue that the performance of a momentum portfolio is not caused by the autocorrelation in the commodity spot prices. Thus, the substantial returns should largely be caused by the long and short legs systematically having long (short) positions in contracts trading in backwardation (contango). However, a zero-cost strategy going long (short) futures contracts trading in backwardation (contango) poses lower average returns when comparing to a pure momentum strategy (Fuertes et al., 2015). This suggests that momentum strategies implemented on commodity futures manage to capture something in addition to the roll returns – similar to the equity momentum strategies, the additional factor is still left unexplained by the current literature.

5.4 Explanations for Momentum

There are multiple explanations for the persistence of the momentum returns, the theories fall into two categories: behavioural and risk based. However, even after nearly 30 years of research, the debate is continuing, and a clear consensus is yet unavailable.

5.4.1 Equity Momentum

The pioneering papers offer investor overreactions as an explanation for the anomaly (Jegadeesh & Titman, 1993; Conrad & Kaul, 1998). They argue that investors overreact to news announcements with a delay. On short- to medium term this pushes the prices of winners (losers) above (below) their long-term intrinsic values. Over a longer period, the prices are expected to return to their fundamental value, thus the returns of the losers should exceed the returns of the winners. The offered explanation is supported by the findings on momentum portfolios posing negative returns over a longer holding period. (Jegadeesh & Titman, 1993; 2001; Asness et al. 2013; 2015).

Additionally, investor underreactions are also considered possible explanation for the anomaly (Frazzini, 2006). Underreactions make new pieces of information incorporate into asset prices more slowly. There are multiple behavioural explanations for this, such as the disposition effect. The disposition effect causes investors to hold on to losers to avoid realizing losses while simultaneously selling the winners early to realize small gains. Asset prices begin to underreact to new information when a large subset of investors is affected by the disposition effect. This in turn causes positive (negative) drift in asset prices after the initial piece of information is released. Frazzini (2006) finds this effect to be pronounced especially at the extremes; stocks currently trading at large losses (gains) for majority of the investors.

However, the findings of Novy-Marx (2012) and Grobys (2016) challenge the over- and underreaction arguments. The seven-month skipping period in a 12-7-1 strategy should give the prices enough time to adjust to their fair value, thus diminishing the effect of investor over- and underreaction. Then again, even these findings may be considered controversial based on the findings of Goyal and Wahal (2015).

The explanation may also lie within the transaction costs. Grundy and Martin (2001) find the profitability of the strategy to diminish severely when accounting for the transaction costs. Only an investor whose transaction costs per one iteration of the strategy are less than 1.5% would have net profits statistically differing from zero (Grundy & Martin, 2001). However, bid-ask spreads along with other direct transaction costs have reduced significantly after the introduction of fully digitalized trading. This may be the reason why Frazzini, Israel and Moskowitz (2012) find transaction costs to be just a small hindrance for large institutional investors with little effect on the strategy performance.

Due to momentum's high turnover, one might also argue that the tax burden must be heavy and thus heavily diminish the returns. However, by construction momentum strategies tend to hold on to winners and sell the losers, thus avoiding short-term realization of capital gains. This makes the strategies relatively tax efficient and is one of the reasons why momentum profits also survive the burden of taxes. (Asness, Frazzini & Israel, 2014.) When considering all the above-mentioned, in the world of digitalized trading, transaction costs (direct or indirect) provide little to no help on explaining the abnormal returns of momentum.

The anomaly may also be explained by the statistical properties of its returns. As found by several researchers, the return distributions on momentum strategies pose excess kurtosis (fat-tails) along with large negative skewness (Ruenzi & Weigert, 2018; Barroso & Santa-Clara, 2015). As discussed in Chapter 5.3, these properties indicate a heightened likelihood of a large negative event, such as several momentum crashes experienced during the 2000s. Naturally, such properties are strongly disliked by investors (Kraus & Litzenberger, 1976). Thus, the substantial excess returns may just be an adequate compensation for *"collecting dimes in front of a steamroller"*. The already discussed findings of Ruenzi and Weigert (2018) support this hypothesis.

5.4.2 Commodity Futures Momentum

Even though less studied, the behavioural explanations used for equity momentum strategies should also be relevant in explaining momentum returns on commodity futures. The explanation should prove to be relevant especially today where the commodity futures markets are considered "financialized" with large amount of funds flowing into the markets in search for yield. As discussed earlier, this development has led to a higher correlation between the commodity futures and equity markets, which should mean that the markets are also driven by similar investor psychology. (Bhardwaj et al., 2015; Tang & Xiong, 2012.)

One puzzling thing about the performance of commodity futures momentum is that the momentum effect seems to reside in only the futures contracts, not in the spot prices of the underlying commodities (Chaves and Viswanathan, 2016). Miffre and Rallis (2007) hypothesize that commodity futures momentum returns are explained by the roll returns on the futures contracts. Based on their findings, momentum strategies buy (short) commodities trading in backwardation (contango), which leads to a positive risk premium for the entire momentum portfolio. This finding is affirmed by Chaves and Viswanathan (2016). However, this hypothesis is contradicted by the findings of Fuertes et al. (2014) who find that the returns on a strategy based solely on the term structure of commodity futures (i.e., placing bets only based on backwardation/contango signals) poses a correlation of 0.2 towards a commodity futures momentum strategy. Based on this, the returns on commodity futures momentum are to some extent explained by the strategy systematically choosing long (short) positions on contracts trading in backwardation (contango).

Gorton et al. (2013) suggest that the key to the puzzle may be in inventory levels. As discussed in chapter 4.1.1., the prices of commodity futures tend to rise (decrease) with decreasing (rising) global inventory levels. Furthermore, global inventory levels adjust slow to shocks making the inventory levels sticky, which creates opportunities for trend following strategies, such as momentum. Gorton et al. (2013) find that the winner (loser) portfolio systematically selects commodities with below (above) normal inventory levels. This suggests that a commodity futures momentum strategy could just be an indirect bet on the level of inventories.

5.5 **Improving Momentum Performance**

Grundy and Martin (2001) propose one of the first attempts at improving the performance of momentum strategies. As discussed in Chapter 5.3, momentum strategies pose significant negative betas towards the overall market during and after bear markets, ultimately resulting in significant negative returns as the market recovers. Grundy and

Martin (2001) propose that the variability of the returns can be reduced drastically by hedging against market and size factors. This is done by estimating long-term (36-month) factor loadings of the strategy from prior data and using the estimates to hedge these exposures (betas) to zero. On average, such hedging strategy increases the average risk-adjusted (two-factor) performance from 0.44% to 0.63% per month. Simultaneously the standard deviation of the monthly returns is reduced nearly a fourth (from 6.90% to 5.35%), thus resulting in a substantial increase in the Sharpe ratio. (Grundy & Martin, 2001.)

Daniel and Moskowitz (2016) show that using a beta hedging strategy is not enough to avoid momentum crashes. An ex-ante hedged portfolio will still have a negative market exposure during post bear market rebounds, resulting in significant losses (Daniel & Moskowitz, 2016). However, Daniel and Moskowitz (2016) propose a new hedging strategy. The rationale behind the strategy lies within the option-like behaviour of the short leg as it uses the expected variance as one of the components. The strategy dynamically weights the momentum portfolio based on return and variance forecasts of the strategy and thus aims to maximize the in-sample Sharpe ratio; it is expressed as follows:

$$w_t = \left(\frac{1}{2\lambda}\right)\frac{\mu_t}{\sigma_t^2} \tag{29}$$

Where μ_t is the expected return on the strategy over the next month, which is derived using preceding six-month strategy return. σ_t^2 is the expected variance over the coming month derived from the variance of past 126 days using a generalized autoregressive conditional heteroskedasticity (GARCH) model. λ is a scalar that controls the risk and return of the hedged portfolio. Here variance has an inverse relationship to the weight of the portfolio; during times of low uncertainty the strategy may get implemented with leverage, thus making the portfolio weight >1.0. During bear markets with high uncertainty the weighting may be negative, thus one would be effectively shorting a momentum portfolio. (Daniel & Moskowitz, 2016.)

When choosing a λ which makes the volatility of the strategy fixed at 19%, the hedging strategy provides promising results in both in-sample and out-of-sample tests. Unsurprisingly, the weights for the hedged portfolio prove to be volatile, ranging from -0.604 to 5.37. However, when controlling for the regular unhedged strategy and the Fama-French three factors, the hedged strategy poses an annualized alpha of 22.04%. In aggregate the hedged strategy poses 1.194 out-of-sample and 1.202 in-sample Sharpe ratios, which were nearly double that of the unhedged strategy Sharpe of 0.682. Additionally, the hedging strategy manages to avoid vast majority of the momentum crashes. (Daniel & Moskowitz, 2016.)

As the risk of momentum varies over time, Barosso and Santa-Clara (2015) propose a hedging strategy where the strategies' volatility is managed. The risk of the strategy is measured by the realized variance (volatility) of the daily returns. Testing the hedging procedure is straight-forward; the portfolio returns get scaled down by using the realized volatility during the previous six months, after this the portfolio returns are scaled to target a constant volatility. However, this procedure causes the weights of the short and long leg to vary, they are no longer equally weighted through time even though the strategy remains zero-cost. The procedure is expressed in **Equation X**, where $\hat{\sigma}_t$ is the volatility forecast based on the realized volatility during the preceding six months, σ_{target} is the desired level of volatility and $R_{WML,t}$ is the return of the portfolio during time t**.** (Barosso & Santa-Clara, 2015.)

$$R_{WML,t\,(scaled)} = \frac{\sigma_{target}}{\hat{\sigma}_t} R_{WML,t} \tag{30}$$

The results for the scaling procedure are promising. Table 6 below presents the summary statistics for a portfolio scaled with an annualized volatility target of 12%. Volatility scaling substantially lowers the maximum drawdown, standard deviation, kurtosis, and skewness of the portfolio. All this is achieved without sacrificing returns – in fact, the volatility scaled portfolio poses nearly 2% higher annualized return and thus a significantly higher Sharpe ratio. (Barosso & Santa-Clara, 2015.)

Table 6. Gains from scaling (Barosso & Santa-Clara, 2015)

	WML	***WML scaled***
µ p.a. (%)	*14.46*	*16.50*
σ p.a. (%)	*27.53*	*16.95*
Sharpe	*0.53*	*0.97*
Max (%)	*26.18*	*21.95*
Min (%)	*-78.96*	*-28.40*
Skew	*-2.47*	*-0.42*
Kurt	*18.24*	*2.68*

The findings of Grobys, Ruotsalainen and Äijö (2018) support the effectiveness of volatility scaling. The performance of an industry momentum strategy (i.e., shorting poor performing industries, going long on thriving industries) greatly increases with volatility scaling. However, the findings suggest that the increasing performance has an inverse relationship towards the length of the time-period used for estimating the volatility forecast. Portfolios scaled using a volatility forecast made from one-month of preceding data present significantly higher average returns than their three- and six-month counterparts. (Grobys et al. 2018.)

The two hedging methods based on strategy volatility cannot be used in the empirical part of this thesis. This is due to the chosen dataset containing only monthly returns, which would significantly affect the volatility forecasts. However, the hedging strategy proposed by Grundy and Martin (2001) is used as it would be implementable with relative ease even by an unsophisticated investor through the usage of various ETFs following the chosen factors.

6 Data & Methodology

The empirical part of this thesis examines the performance of dual momentum portfolios containing a monthly return series from both equity and commodity futures momentum strategies. The purpose of this chapter is to introduce the reader to the data used and the methodology applied to draw inference on the research questions.

6.1 Data Description

The data on the regular equity momentum strategy is obtained from Kenneth French's (2020) database. The constructed monthly timeseries follows an equally weighted portfolio using the 12-1-1 strategy with long (short) positions in the top (bottom) return percentiles (10%s). The strategy is implemented on the U.S. equities included on NYSE, AMEX and NASDAQ exchanges on a sampling period spanning from January 1st, 1990 to December 31st, 2019.

The data on the commodity futures momentum is obtained from AQR (2020) database. This momentum portfolio is the same as the one in the paper of Asness et al. (2013). It is constructed on pricing data from 27 different commodity futures, all of which are obtained from several sources. The data on industrial metals is from the London Metal Exchange (LME) whereas the data on precious metals is from New York Commodities Exchange (COMEX), the pricing data on Platinum is retrieved from Tokyo Commodity Exchange (TOCOM). The data on Lean Hogs in addition to Live and Feeder Cattle futures is from the Chicago Mercantile Exchange (CME). The pricing data on the other agricultural commodities (Wheat, Corn, Soy, Soy Meal and Soy Oil) is from the Chicago Board of Trade (CBOT). The data on WTI Crude, Gasoline, Heating Oil and Natural Gas is from New York Mercantile Exchange (NYMEX). Pricing data on Coffee, Sugar, Cocoa and Cotton is retrieved from New York Board of Trade (NYBOT).

The returns on these futures are calculated by compounding the daily excess returns on the most liquid contracts (often the nearest or second nearest to maturity) to arrive at a monthly return series. These monthly return series are then used to construct 12-1-1 momentum portfolios. The equally weighted portfolios invest in the top (bottom) 30% deciles based on the raw cumulative returns 12-months prior (Asness et al. 2013).

For the regressions and comparisons, this thesis uses the FF3 and FF6 models in addition to the monthly return on the S&P GSCI total return index. The monthly data for the factor models is obtained from Kenneth French's database (2020).

The FF3 excess market return (Rm-Rf) is the monthly return on a value weighted portfolio including all US incorporated firms listed on the NYSE, AMEX or NASDAQ exchanges minus the one-month Treasury bill rate. The FF3 factors are formed by using 6 value weighted portfolios based on size and book-to-market. The SMB factor is the average return on three small portfolios (Value, Neutral, Growth) minus the average return on their big counterparts. The HML factor is the average return on two value portfolios (Small & Big Value) minus the average return on two growth portfolios (Small & Big Growth). Notably, all the factor portfolios contain stocks listed on the NYSE, AMEX and NASDAQ exchanges.

The excess market return and HML factor are the same in the FF6 model as in the FF3 model. However, the SMB factor differs slightly in its composition, here it is the return on nine small portfolios minus the return on nine big portfolios. The RMW factor is the average return on two (Small & Big) robust profitability portfolios minus the return on two weak profitability portfolios. The CMA factor is the average return on two conservative (Small & Big) investment behaviour portfolios minus the average return on two aggressive investment behaviour portfolios. The momentum factor is the average return on two (Small & Big) high prior return (top 70th return percentile) portfolios minus the average return on two low prior return portfolios (bottom 30th percentile). Again, all the factor portfolios contain stocks listed on the NYSE, AMEX and NASDAQ exchanges.

To account for the commodity market risk, the monthly total returns on the S&P GSCI are included in regressions for the commodity futures momentum strategies and the constructed dual portfolios. This return series is included as a fourth (seventh) factor for the FF3 and FF6 regressions. The S&P GSCI total return index time-series is obtained from Datastream.

Table 7 presents the descriptive statistics on the underlying indices used for the momentum strategies. During the thirty-year period (01/90 – 12/19), a single dollar invested the U.S. equity markets would on average have earned 10.71% annualized, cumulating up to $16.76 by the end of the sample. The annualized market volatility during this time nears 15%, which is makes the market's Sharpe ratio 0.73. Unsurprisingly, as in the literature, the market's correlation to the 12-1-1 equity strategy nears zero which is essentially long (short) on the top (bottom) return percentiles of the market portfolio. The market portfolio poses only slight negative skewness, its highest monthly drawdown occurred during November of 2008 in midst of the Financial Crisis.

Table 7. Descriptive statistics

	S&P GSCI	***FF Market***
μ total (%)	*37.06*	*1676.86*
μ p.a. (%)	*3.23*	*10.71*
t-stat	(0.84)	(3.94)
σ p.a. (%)	*20.74*	*14.63*
Sharpe	*0.16*	*0.73*
ρ to Equity	*-0.19*	*-0.01*
Min (%)	*-28.20*	*-17.15*
Max (%)	*22.94*	*11.35*
Skew	*-0.68*	*-0.16*
Kurt	*1.26*	*1.87*

The annualized returns on the S&P GSCI index are low at 3.23% annualized, due to heightened volatility are statistically indistinguishable from zero. Additionally, the high volatility makes the Sharpe of the index 0.16, which is less than a fourth of the equity market Sharpe during the same period. A single dollar invested in the GSCI would have cumulated to $1.37 by the end of the sample. The cumulative returns peak at $5.58 in

June of 2008, during the commodity market melt-up which preceded the Financial Crisis. The distribution of the monthly returns poses higher negative skewness than its equity counterpart. This is especially seen in the worst drawdown for the index, which is nearly double that of its equity counterpart. The worst drawdown is also during the Financial Crisis in October of 2008. The index correlation to the 12-1-1 equity strategy is well within the negative territory, which would already lead to notable diversification benefits.

6.2 Methodology

First, the descriptive statistics and the return distributions are under examination. The strategy performance is also examined in several subsamples to get a more robust look on the evolution of the individual strategy performance and their cross-correlation through time. The possible strategy alphas are uncovered by running multivariate regressions on the FF3 and FF6 models. The regressions on the commodity futures momentum strategies include the total returns on S&P GSCI as an explanatory variable as their return series are suspect to the overall commodity market risk.

Additionally, this thesis uses the risk management method proposed by Grundy and Martin (2001) on both strategies. Volatility scaling measures are not used due to recent contradictory results on their performance (Liu et al., 2019) in addition to the commodity data being only available in a monthly format.

The beta hedging method is implemented by regressing the past 36-month returns of the strategy on the returns of the FF3 factors (using market return instead of Rm-Rf). Based on the regression results, the strategy aims to nullify the Beta exposures for the coming month, ultimately forming a hedged return series (R'_{WML_t}) which is expressed as follows:

$$R'_{WML_t} = R_{WML_t} - \beta_{Mkt(t-36)} R_{Mkt_t} - \beta_{SMB(t-36)} SMB_t - \beta_{HML(t-36)} HML_t \quad (31)$$

In the literature commodity futures momentum strategies are often only regressed towards the GSCI and the overall equity market as the strategies should not be affected by the factors concerning value and firm-size effects (Miffre & Rallis, 2007). Thus, the commodity futures momentum strategy is hedged through regressing it against the overall equity market and the S&P GSCI, making the return on the hedged strategy:

$$R'_{WML_t} = R_{WML_t} - \beta_{Mkt(t-36)} R_{Mkt_t} - \beta_{GSCI(t-36)} GSCI_t \quad (32)$$

The performance of the hedged strategies is examined in the same manner as their unhedged counterparts.

The individual unhedged and hedged momentum strategies are then used to form two portfolios, one using the unhedged strategies and the other the hedged. The portfolios are built based on the principles of Markowitz' (1952) portfolio theory. The individual momentum strategy weights in the portfolio are chosen in a way which maximizes the portfolio in-sample Sharpe ratio. Thus, the portfolios under examination can be considered the optimal portfolios for the sample period. The regressions on the commodity futures momentum strategies and constructed dual portfolios include the total returns on S&P GSCI as an explanatory variable as their return series are suspect to the overall commodity market risk.

These portfolios are then analysed in the same manner as the strategies earlier. The possible diversification benefits, i.e., an increase in risk-adjusted return is examined through comparing the strategy-portfolio Sharpe ratios using the Ledoit-Wolf (2008) Sharpe test. Additionally, the difference between the strategy-portfolio alphas is tested when running the modified FF3 and FF6 regressions for the portfolios. The difference in the alphas is tested using a simple alpha spread test:

$$t = \frac{\propto_P - \propto_S}{\sqrt{SE^2_{\propto_P} + SE^2_{\propto_S}}} \tag{33}$$

where $\propto_P$ is the alpha of the portfolio, $\propto_S$ is the alpha of the equity momentum strategy, $SE^2_{\propto_P}$ is the standard error of the portfolio's alpha and $SE^2_{\propto_S}$ is the standard error of the equity strategies alpha, respectively.

An optionality regression is run to see whether diversification affects momentum crashes. The regression aims to uncover any option-like behaviour within the individual strategies and in the portfolio formed out of them (Daniel and Moskowitz, 2016):

$$R_{WML_t} = \propto + \beta_{Mkt_t} R_{Mkt_t} + \beta_B I_{B_{t-1}} R_{Mkt_t} + \beta_U I_{B_{t-1}} I_{U_t} R_{Mkt_t} \tag{34}$$

The return of the strategies (portfolios) is regressed against the overall market (FF market factor or the GSCI). The variable $I_{B_{t-1}}$ is an ex-ante bear market indicator, it receives a value of one if the preceding 24-month market return is negative, being zero otherwise. I_{U_t} is another binary variable, it receives a value of one if the current month's market return is positive. Thus, the third beta coefficient captures the strategy behaviour during post bear market reversals.

The last regression examines whether the individual strategies or the portfolio are significantly exposed to fluctuations in stock market volatility or overall market liquidity. These two factors are found significantly influencing the performance of pure equity momentum strategies. Momentum returns pose a positive (negative) exposure to overall market volatility (liquidity) (Daniel & Moskowitz, 2016; Butt & Virk, 2017). The VIX is used as a proxy for market volatility whereas the TED spread is used as a proxy for market liquidity. The TED spread measures the spread between the three-month U.S. T-bill and the three-month LIBOR, which is the average interbank lending rate. A widening TED spread tells of decreasing liquidity and increasing solvency concerns in the interbank market; here the spread is used as a proxy for market liquidity. The VIX measures the implied volatility in the S&P500 options market, it is a gauge of market expectations on the S&P500 future 30-day volatility. Here it is used as a proxy for overall market volatility. The regression is expressed as follows:

$$R_{WML_t} = \beta_{TED_t} TED_t + \beta_{VIX_t} VIX_t \tag{35}$$

Where R_{WML_t} is the month t return on one of the individual hedged or unhedged (equity or commodity futures) momentum strategies or the return on the constructed hedged or unhedged portfolio. TED_t is the index level on the TED spread during month t and VIX_t is the index level of the VIX-index during month t.

7 Empirical Research

This chapter implements the described methodology on the datasets. First, the performance of the individual unhedged and hedged strategies is under examination. Afterwards the portfolios are constructed, and their properties examined.

7.1 Individual Strategies

Table 8 presents the descriptive statistics for the two momentum strategies, the cumulative returns on these strategies are presented in Figure 8. The 12-1-1 equity momentum strategy (from now on abbreviated as EQMOM) poses a 0.45% higher average annualized excess return when comparing to its counterpart implemented on commodity futures (from now on abbreviated as CFMOM) (7.60% vs. 7.15%). However, the average return does not tell the entire story as the cumulative return on the CFMOM strategy nearly doubles that of the EQMOM strategy. A single dollar invested in CFMOM would cumulate to $5.21 during the 30-year sample, whereas the same investment in EQMOM strategy would end the sample at $3.20. The cumulative returns for CFMOM strategy peak at $10.61 in June of 2008. The EQMOM strategy cumulative returns peak at $5.56 in December of 2000, just a month before the disastrous -59.95% crash of January 2001. The EQMOM strategy nearly manages to take out its 2000 high by the end of 2008, reaching $5.08 just before crashing below $1 during the next 12-month period. The last two years of the sample are disastrous for the CFMOM strategy, as it loses nearly 40% of its cumulative returns within this period.

	CFMOM	*EQMOM*
μ total (%)	*421.13*	*219.87*
μ p.a. (%)	*7.15*	*7.60*
t-stat	(2.13)	(1.66)
σ p.a. (%)	*18.06*	*24.73*
Sharpe	*0.40*	*0.31*
ρ to Equity	*0.20*	*1.00*
Min (%)	*-25.20*	*-59.95*
Max (%)	*22.11*	*19.30*
# Drawdowns	*10*	*17*
Skew	*-0.11*	*-2.80*
Kurt	*2.52*	*18.29*

Table 8. Unhedged strategies

Interestingly, the annualized volatility for the CFMOM strategy is notably below its underlying index, the GSCI. Additionally, it is also below the EQMOM strategy volatility (18.06% vs. 24.73%). Additionally, the CFMOM strategy volatility is well below the volatility of the 12-1-1 commodity futures strategy in the paper of Miffre and Rallis (2007) (18.06% vs. 25.57%). The notable differences in strategy volatilities lead to the CFMOM strategy outperforming its counterpart when performance is measured with Sharpe ratio.

As expected, the return distribution of the EQMOM strategy poses high excess kurtosis and negative skewness (-2.80 & 18.29), thus clearly presenting the strategy crash risk. The negative skewness is shown in the sheer number of drawdowns for the strategy; over the entire sample the EQMOM strategy has 17 occurrences of a monthly drawdown larger than -10%. The return distribution for the CFMOM strategy poses only slight negative skewness at -0.11, which is especially surprising when the skewness for underlying index (the GSCI) during the same period is -0.68. The strategy only has 10 occurrences of monthly drawdowns larger than -10%, which is a clear improvement when comparing to EQMOM. The distribution for CFMOM is also fat-tailed, but to a much lesser extent than its equity counterpart as it poses a kurtosis of 2.52.

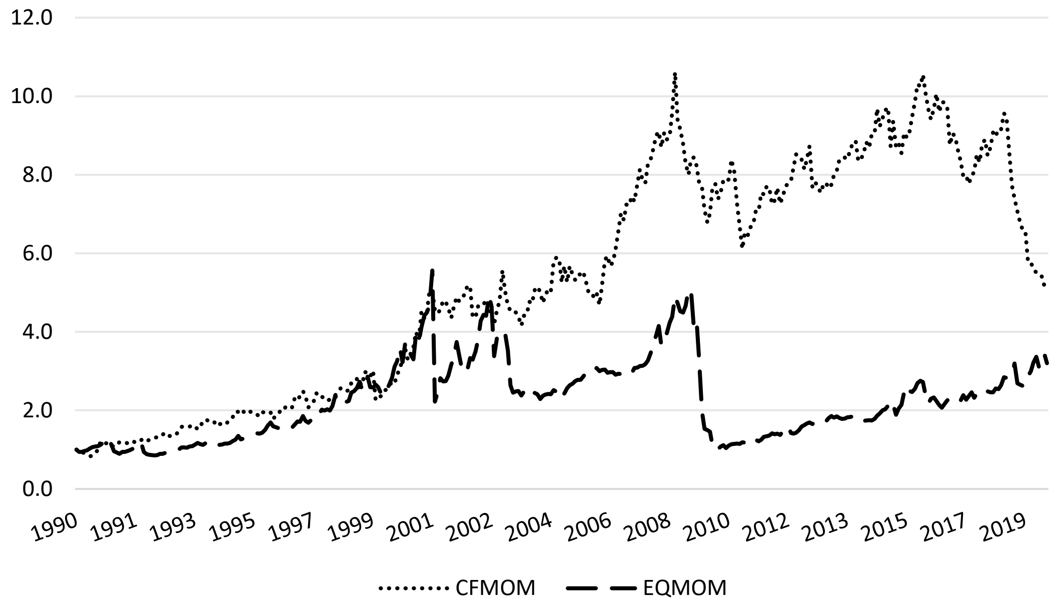

Figure 8. Unhedged strategy cumulative returns

The cross-strategy correlation for the entire sample is at a modest level of 0.20, which already hints of an opportunity to obtain notable diversification benefits upon portfolio formation.

Table 9. Strategy five worst drawdowns

Panel A	***EQMOM***	***CFMOM***
01/2001	*-59.95*	*-10.00*
04/2009	*-40.36*	*-1.39*
11/2002	*-27.19*	*-4.37*
05/2003	*-24.88*	*-2.51*
08/2009	*-24.68*	*9.78*
Correlation	*0.67*	
Panel B	***CFMOM***	***EQMOM***
03/1999	*-25.20*	*2.66*
03/2002	*-15.33*	*-1.28*
02/1997	*-12.17*	*-2.63*
09/2012	*-12.08*	*-2.24*
07/2008	*-11.54*	*-3.72*
Correlation	*-0.98*	

Panel A summarizes the months with worst drawdowns for the EQMOM strategy while presenting the respective returns of the CFMOM strategy on the same day. **Panel B** summarizes the months with worst drawdowns for the CFMOM strategy while presenting the respective returns of the EQMOM strategy on the same day.

Table 9 above depicts the five worst drawdowns for the momentum strategies. Panel A (B) of the table contains the worst monthly drawdowns for the EQMOM (CFMOM) strategy while showing the return on CFMOM (EQMOM) during the same month. Most notably, the worst drawdowns for the strategies do not occur during the same month. Additionally, the table further pinpoints the difference in the strategy return distributions discussed earlier in this chapter: the worst five drawdowns for CFMOM are much lower than the ones for EQMOM. Overall, it seems that if EQMOM crashes, CFMOM has a tendency of also posing a negative return (correlation of 0.67). Furthermore, when CFMOM crashes, EQMOM most often poses a slight negative return for the month (correlation of -0.98). Based on the table, one can conclude that diversifying an equity only momentum portfolio by including a commodity futures momentum strategy should not have a major impact on the momentum crashes experienced during the 2000s. However, it must be noted that these correlations should be taken with a grain of salt, as they are obtained from a sample of five drawdowns.

Table 10 contains the descriptive statistics for the two hedged strategies which were hedged using the using the procedure described in the chapter prior.

Table 10. Hedged strategies

	CFMOM (H)	*EQMOM (H)*
μ total (%)	*724.34*	*821.83*
μ p.a. (%)	*8.80*	*11.42*
t-stat	(2.54)	(2.42)
σ p.a. (%)	*18.65*	*25.46*
Sharpe	*0.47*	*0.45*
ρ to Equity	*0.20*	*1.00*
Min (%)	*-22.77*	*-63.97*
Max (%)	*23.19*	*21.41*
# Drawdowns	*8*	*14*
Skew	*-0.12*	*-2.73*
Kurt	*1.80*	*19.62*

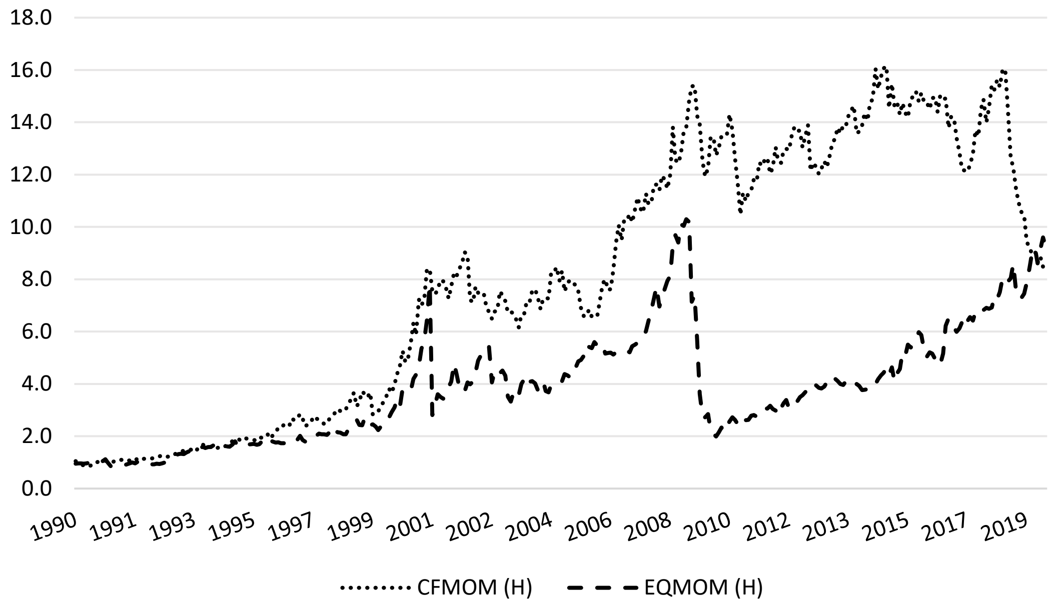

Figure 9. Hedged strategy cumulative returns

Figure 9 illustrates the cumulative returns on these strategies over the entire 30-year sample. The beta hedging procedure has a significant effect on both momentum strategies. However, as shown by Daniel and Moskowitz (2016), it does not dampen the momentum crashes, which are still clearly visible in the descriptive statistics in addition to the figure above. Overall, the beta hedged equity momentum strategy (abbreviated as EQMOM (H) from now on) experiences a 50% increase in its average annualized returns, increasing from 7.60% p.a. to 11.42% for the hedged strategy. The cumulative return for EQMOM (H) is nearly four times higher than the one for unhedged EQMOM strategy. A single dollar invested in this strategy would cumulate into $9.22 by the end of the sample, peaking at $10.29 in November of 2008, just before the momentum crash. The average annual return on the hedged commodity futures momentum strategy (abbreviated as CFMOM (H) from now on) also improves to 8.80% from the earlier 7.15%. A single dollar invested into the strategy would cumulate to $8.24 by the end of the sample, peaking at $16.02 just before the strategy begins its downturn in early 2018.

Both hedged strategies pose similar volatilities to their unhedged counterparts, making the Sharpe ratios higher for both strategies. As pointed out earlier, the hedge has little effect on the negative skewness of the equity momentum strategy, which remains elevated at -2.73 for EQMOM (H). Additionally, the kurtosis nears 20 this time, promoting the notion that extreme deviations remain likely for this strategy, regardless of the hedge put in place. This is especially visible in the worst monthly drawdown, which now nears 64%. The CFMOM (H) strategy poses slightly lower negative skewness and excess kurtosis when comparing to its unhedged counterpart (CFMOM), its extreme values remain in the same ballpark. However, the hedge manages to lower the amount of large (>10%) drawdowns for both strategies; the EQMOM (H) experiences 14 drawdowns, down from 17 for its unhedged counterpart. Additionally, CFMOM (H) now only experiences 8 drawdowns larger than 10%, down from the earlier 10 of the unhedged CFMOM strategy. The correlation between the strategies remains unaffected by the hedging procedure, thus, a portfolio formed out of these two strategies will likely outperform the unhedged one.

Table 11. Hedged strategy five worst drawdowns

Panel A	***EQMOM (H)***	***CFMOM (H)***
01/2001	*-63.97*	*-10.13*
04/2009	*-36.20*	*-2.26*
01/2009	*-29.86*	*3.61*
11/2002	*-25.18*	*-3.80*
05/2009	*-24.36*	*-10.35*
Correlation	*0.38*	
Panel B	***CFMOM (H)***	***EQMOM (H)***
03/1999	*-22.77*	*1.79*
03/2002	*-19.02*	*-1.91*
09/1998	*-14.18*	*6.05*
11/2018	*-12.93*	*1.58*
09/2012	*-12.64*	*-2.11*
Correlation	*0.07*	

Panel A summarizes the months with worst drawdowns for the EQMOM (H) strategy while presenting the respective returns of the CFMOM (H) strategy on the same day. **Panel B** summarizes the months with worst drawdowns for the CFMOM (H) strategy while presenting the respective returns of the EQMOM (H) strategy on the same day.

As earlier, Table 10 above depicts the five worst drawdowns for the hedged momentum strategies. Panel A (B) of the table contains the worst monthly drawdowns for the EQMOM (H) (CFMOM (H)) strategy while showing the return on CFMOM (H) (EQMOM (H)) during the same month. As earlier with the unhedged momentum strategies, the worst drawdowns for the individual hedged strategies do not occur during the same month. In contrast to earlier, the correlation between EQMOM (H) and CFMOM (H) when EQMOM (H) crashes is much lower at 0.38 where it was 0.67 for the unhedged momentum strategies. Furthermore, when CFMOM (H) crashes, EQMOM (H) poses mostly uncorrelated returns, whereas the correlation was -0.98 for the unhedged momentum strategies (see Table 9). However, it must be noted that these correlations should be taken with a grain of salt, as they are obtained from a sample of five drawdowns.

7.1.1 Subsamples

Table 12 presents the descriptive statistics for the hedged and unhedged strategies during various subsamples.

Table 12. Individual strategy subsamples

Panel A: Unhedged strategies	*μ p.a. (%)*	*t-stat*	*σ p.a. (%)*	*R2R*	*Worst 6m (%)*	*Best 6m (%)*	*Skew*	*Kurt*	*ρ to EQMOM*
Period A: 01/1990-12/1999									
CFMOM	*13.16*	(2.25)	*18.47*	*0.71*	*-20.49*	*39.41*	*-0.56*	*5.79*	*0.04*
EQMOM	*14.33*	(2.63)	*17.24*	*0.83*	*-26.81*	*39.73*	*-0.84*	*2.89*	
Period B: 01/2000-12/2006									
CFMOM	*14.42*	(1.76)	*21.67*	*0.67*	*-21.26*	*39.23*	*0.29*	*0.35*	*0.34*
EQMOM	*5.30*	(0.40)	*34.84*	*0.15*	*-48.19*	*49.44*	*-2.85*	*15.96*	
Period C: 01/2007-12/2009									
CFMOM	*4.19*	(0.43)	*16.73*	*0.25*	*-20.87*	*24.90*	*-0.06*	*-0.10*	*0.22*
EQMOM	*-23.77*	(1.09)	*37.81*	*-0.63*	*-74.53*	*32.10*	*-1.83*	*3.43*	
Period D: 01/2010-12/2014									
CFMOM	*5.02*	(0.82)	*13.73*	*0.37*	*-23.05*	*17.30*	*-1.02*	*1.29*	*0.04*
EQMOM	*12.70*	(2.57)	*11.06*	*1.15*	*-28.39*	*20.16*	*-0.75*	*1.53*	
Period E: 01/2015-12/2019									
CFMOM	*-11.10*	(1.67)	*14.84*	*-0.75*	*-30.49*	*20.50*	*-0.44*	*-0.04*	*0.18*
EQMOM	*11.09*	(1.27)	*19.46*	*0.57*	*-21.59*	*30.70*	*-0.60*	*0.75*	

Note: The table continues on the next page.

Panel B: Hedged strategies	*μ p.a. (%)*	*t-stat*	*σ p.a. (%)*	*R2R*	*Worst 6m (%)*	*Best 6m (%)*	*Skew*	*Kurt*	*ρ to EQMOM (H)*
Period A: 01/1990-12/1999									
CFMOM (H)	*16.57*	(2.85)	*18.37*	*0.90*	*-20.82*	*37.45*	*-0.91*	*2.93*	*0.10*
EQMOM (H)	*13.70*	(2.59)	*16.70*	*0.82*	*-25.03*	*43.16*	*-0.43*	*0.42*	
Period B: 01/2000-12/2006									
CFMOM (H)	*14.87*	(2.04)	*23.05*	*0.65*	*-17.38*	*49.80*	*0.34*	*1.07*	*0.29*
EQMOM (H)	*15.10*	(1.33)	*36.01*	*0.42*	*-54.48*	*86.22*	*-3.08*	*18.69*	
Period C: 01/2007-12/2009									
CFMOM (H)	*10.68*	(1.88)	*18.00*	*0.59*	*-20.27*	*34.43*	*0.18*	*0.51*	*0.28*
EQMOM (H)	*-17.62*	(1.42)	*39.33*	*-0.45*	*-73.45*	*39.29*	*-1.71*	*2.33*	
Period D: 01/2010-12/2014									
CFMOM (H)	*4.55*	(1.01)	*14.21*	*0.32*	*-23.13*	*17.57*	*-0.90*	*1.16*	*0.08*
EQMOM (H)	*13.94*	(3.06)	*14.39*	*0.97*	*-23.95*	*36.83*	*-0.21*	*-0.12*	
Period E: 01/2015-12/2019									
CFMOM (H)	*-12.14*	(2.59)	*14.80*	*-0.82*	*-34.07*	*22.91*	*-0.33*	*0.25*	*0.14*
EQMOM (H)	*16.61*	(2.70)	*19.46*	*0.85*	*-17.23*	*31.51*	*0.26*	*1.71*	

Panel A illustrates the descriptive statistics for the unhedged strategies during the selected subsamples.
Panel B illustrates the descriptive statistics for the **hedged** strategies during the selected subsamples.

During the first 10-year period, the CFMOM strategy poses an annualized return of 13.16% with a volatility of 18.47%, making the strategy Sharpe 0.71. The EQMOM strategy edges slightly above, posing a Sharpe of 0.83 at an annualized return (volatility) of 14.33% (17.24%). The worst six-month drawdown was 20.50% (26.80%) for CFMOM (EQMOM) strategy, respectively. The best six-month periods are nearly identical for both strategies, both gaining nearly 40% within such a short time span. The performance of the EQMOM (H) is slightly inferior to that of the unhedged strategy, posing an annualized return of 13.70% with a slightly lower volatility of 16.70%. However, the biggest difference is in the distribution of the returns; both, the negative skewness and kurtosis reduce substantially from -0.84 to -0.43 and from 2.89 to 0.42. The CFMOM (H) strategy also poses near 30% increase in its Sharpe ratio (0.71 vs. 0.90) as its annualized return increases to 16.57% while the volatility remains near stagnant. However, the hedging procedure increases the cross-strategy correlation from 0.04 (CFMOM & EQMOM) to 0.10 (CFMOM (H) & EQMOM (H)).

The EQMOM and EQMOM (H) strategies' performance hinders notably for the second period ranging from 2000 to 2006. This is mostly due to the violent momentum crash occurring in January of 2001, where nearly 60% of the strategy cumulative returns are wiped out in a single month. The effect of this crash is especially visible in the high negative skewness and excess kurtosis of the return distribution. However, here the hedging procedure results in a drastic increase in strategy performance as the EQMOM (H) strategy has its annualized returns nearly tripled (5.30% vs. 15.10%). As discussed earlier, the hedge does not manage to dampen the momentum crash; the distribution of returns for EQMOM (H) still poses high negative skewness and excess kurtosis. This is also visible in the worst six-month drawdown, which is at -54.48%, some 6% higher than the -48.19% drawdown for EQMOM. However, such crash risk is not carried without a reward; during the period, the best six-months for the unhedged (hedged) strategy return 49.44% (86.22%). The CFMOM strategy continues its robust performance in this period, posing an average annualized return of 14.42%. However, its volatility for this period is slightly higher at 21.67%, making the strategy Sharpe 0.67. Interestingly, the return distribution for CFMOM poses positive skewness for this period. Unlike its equity counterpart, the CFMOM (H) strategy performs worse across all metrics for this period. The cross-strategy correlation is at its peak during this period at values of 0.34 (0.29) for the unhedged (hedged) strategies.

The third period covers the years of the Financial Crisis (2007-2009). Towards the end of this period, the EQMOM strategy experiences the worst momentum crash in the history, which occurs as the market starts rebounding in early to mid-2009. On average, the strategy loses 23.77% annualized while its worst six-month drawdown is at a disastrous 74.53%. The EQMOM (H) strategy fares slightly better but still poses a significant negative annualized return at -17.62%. As in the earlier period, the hedge does not affect the severity of the crash which remains above 73%. Both commodity futures momentum strategies pose positive returns for this period at 4.19% for CFMOM and 10.68% for the CFMOM (H) strategy, respectively. However, statistically the return on CFMOM strategy does not differ from zero. The worst six-month drawdown for both strategies is just above 20%. Additionally, during this turbulent period, the level of volatility remains near the entire sample average at 16.73% (CFMOM) and 18.00% (CFMOM (H)). Interestingly, the return distribution for the hedged strategy poses positive skewness during the period. Thus, having a diversified portfolio might substantially mitigate the strategy crash risk during the period.

In the post crisis period both equity momentum strategies quickly return to their double-digit annualized returns, posing returns of 12.70% (EQMOM) and 13.94% (EQMOM (H)) for the first five-year period. The good performance continues in the last subperiod ranging from 2015 to the end of 2019, where the strategies return 11.09% (EQMOM) and 16.61% annualized (EQMOM (H)). The annualized volatilities range from 11.06% to 19.50% during both subperiods, making the strategy Sharpes range between 0.57 and 1.15. During the last period, the EQMOM (H)'s best six-month period is nearly 50% higher than its worst drawdown (31.51% vs. -17.23%). Such performance is especially visible in the return distribution for EQMOM (H), which becomes positively skewed for the first time in the entire sample.

The CFMOM and CFMOM (H) strategies' performance starts to hinder after the crisis. The strategies return 5.02% (CFMOM) and 4.55% (CFMOM (H)) annualized while posing volatilities of 13.73% and 14.21% during the first five-year period. However, these returns do not statistically differ from zero. Additionally, the strategies' return distributions pose the highest negative skewness out of all subsamples during the 2010-2014 period. The correlation towards the respective equity momentum strategy still remains near-zero for both strategies during this subsample. However, as discussed earlier, the commodity momentum strategies start crashing during the beginning of 2018, making the annualized returns for the last five-year period -11.10% (CFMOM) and -12.14% (CFMOM (H)).

7.1.2 Regressions

The results on the modified FF3 and FF6 regressions with the alphas annualized are presented in Table 13. As often with financial data, this data is also heteroskedastic, the heteroskedasticity consistent t-statistics are presented in the parentheses.

Table 13. FF3 and FF6 regressions

	CFMOM	***EQMOM***	***CFMOM (H)***	***EQMOM (H)***
Panel A: Fama-French Three Factors and GSCI				
Alpha (%)	***7.5*****	***11.1******	***10.0******	***12.9******
	(2.26)	(2.54)	(2.88)	(2.78)
GSCI	*0.185***		*0.015*	
	(2.23)		(0.20)	
Mkt	*-0.108*	*-0.322****	*- 0.143**	*- 0.236**
	(1.48)	(2.77)	(1.74)	(1.92)
SMB	*0.057*	*-0.212*	*0.09*	*0.087*
	(0.52)	(1.03)	(0.74)	(0.40)
HML	*-0.075*	*-0.320*	*-0.14*	*0.149*
	(0.74)	(1.43)	(1.19)	(0.61)
R2	*0.05*	*0.06*	*0.02*	*0.02*
Panel B: Fama-French Six Factors and GSCI				
Alpha (%)	*4.1*	*-3.7*	***6.7****	*-1.9*
	(1.15)	(1.04)	(1.82)	(0.64)
GSCI	*0.173*		*0.005*	
	(2.19)		(0.07)	
Mkt	*0.026*	*0.211****	*-0.003*	*0.318****
	(0.34)	(2.48)	(0.04)	(4.70)
SMB	*0.071*	*-0.149*	*0.085*	*0.100*
	(0.55)	(1.43)	(0.65)	(1.14)
HML	*-0.119*	*0.071*	*- 0.245**	*0.426****
	(0.92)	(0.51)	(1.84)	(3.62)
RMW	*0.116*	*0.457****	*0.080*	*0.344****
	(0.70)	(3.94)	(0.42)	(2.92)
CMA	*0.250*	*0.053*	*0.399***	*0.368****
	(1.35)	(0.24)	(1.96)	(2.21)
UMD	*0.218****	*1.290****	*0.194****	*1.276****
	(3.44)	(11.03)	(2.65)	(23.77)
R2	*0.09*	*0.72*	*0.06*	*0.64*

Note: *, ** and *** denotes significance at the 10%, 5% and 1% levels.

All strategies pose significant positive alphas (at levels of 1% and 5%) when corrected for the FF3 model. Consistent with the findings made earlier, both hedged strategies outperform their unhedged counterparts. Similar to the findings of Miffre and Rallis (2007), the CFMOM strategy poses a significant positive exposure to the GSCI. This exposure becomes insignificant once the strategy is beta hedged (CFMOM (H)'s exposure towards GSCI is insignificant), which suggests that the hedging procedure may work for the whole sample, as one of its goals is to make the strategy beta neutral towards the GSCI. However, regardless of the hedge, the CFMOM (H) strategy poses a slight negative beta (-0.143) towards the FF market factor. The EQMOM strategy has a significant negative beta towards the overall market (-0.322) which directly contradicts some of the earlier findings on momentum market neutrality (e.g., Jegadeesh & Titman, 1993; 2001). However, the significant negative beta may be caused by the severe bear markets included in the sample, as momentum strategies often pose significant negative market betas during such times (Daniel & Moskowitz, 2016). The hedging procedure does not manage to nullify the market beta, as the EQMOM (H) strategy still poses a significant negative beta towards the market. However, the slope of the coefficient is reduced nearly by a third to -0.236. As in the earlier literature, the FF3 model poorly explains the expected returns on the strategies with the R-squared statistics all being below 0.06.

As expected, when correcting for the FF6 factors, the alphas on the equity strategies become insignificant. Interestingly, the market beta for both strategies' changes sign, being a positive 0.211 for EQMOM and 0.318 for EQMOM (H), respectively. Additionally, EQMOM (H) poses a high coefficient towards the HML factor (0.426) while EQMOM's beta towards the factor remains insignificant. Both strategies also pose significant betas towards the RMW profitability factor. The strategies are heavily affected by the UMD factor with highly significant beta coefficients of 1.290 and 1.276. This is not surprising, as by construction the strategies and the UMD factor overlap; the strategy contains the same stocks which are included in the UMD factor's top (bottom) 10^{th} percentiles. This leads to high R-squared statistics for the FF6 model with values as high as 0.72 and 0.64.

Only the CFMOM (H) strategy poses an annualized alpha of 6.70% at the 10% level. When corrected for the FF6 factors, the two commodity futures momentum strategies are no longer significantly affected by the GSCI. The CFMOM strategy only significantly affected by the UMD factor. Additionally, the CFMOM (H) strategy is also affected by this factor: both strategies pose betas nearing 0.20 towards the UMD factor. Such coefficients tell the same story as the cross-strategy correlations examined in the chapter prior which were both 0.20 over the entire sample. CFMOM (H) also poses a beta of 0.399 towards the CMA factor. It seems that the hedging procedure makes both strategies (equity and commodity) exposed to this factor, as the insignificant exposures to this factor become highly significant (at 5% and 1% levels) once the hedge is implemented. For the commodity futures momentum strategies, the R-squared values increase for the modified FF6 model. However, the statistics are both still below 0.10 and thus one can conclude that this model might not be optimal for explaining the returns on the commodity futures momentum strategies.

7.2 Portfolios

Table 14 presents the descriptive statistics on the portfolios constructed out of the unhedged and hedged momentum strategies examined in the chapter prior. From now on, the portfolio formed out of the unhedged (hedged) momentum strategies is abbreviated as COMBO (COMBO (H)). The strategy weights in the portfolio are chosen so that they maximize the in-sample Sharpe ratio. The COMBO portfolio has a third allocated to the EQMOM strategy and the remaining two thirds to the CFMOM strategy. The COMBO (H) has a slightly higher portion allocated in the EQMOM (H) at 41% of the total portfolio while the rest of the portfolio is allocated in CFMOM (H).

Table 14. Combined portfolios

Weights	***COMBO*** ***0.33e 0.67c***	***COMBO (H)*** ***0.41e 0.59c***	***Difference COMBO - EQMOM***	***Difference COMBO (H) - EQMOM (H)***
μ total (%)	*504.61*	*1144.37*	*284.73*	*322.54*
μ p.a. (%)	*7.30*	*9.86*	*-0.30*	*-1.56*
t-stat	(2.48)	(3.20)	(0.09)	(0.28)
σ p.a. (%)	*15.87*	*16.57*	*- 8.86****	*- 8.89****
Sharpe	*0.46*	*0.59*	*0.15*	*0.15*
Min (%)	*-26.64*	*-31.92*	*33.31*	*32.05*
Max (%)	*15.74*	*16.89*	*-3.56*	*-4.51*
# Drawdowns	*7*	*8*	*- 10****	*- 6***
Skew	*-0.74*	*-1.05*	*2.07*	*1.68*
Kurt	*4.40*	*7.10*	*-13.89*	*-12.52*

The last two columns of the table compare the descriptive statistics of the portfolios to the descriptive statistics of the respective equity momentum strategies. These columns aim to shed light on the question “does a portfolio outperform a simple equity momentum strategy?” **Note:** *, ** and *** denotes significance at the 10%, 5% and 1% levels.

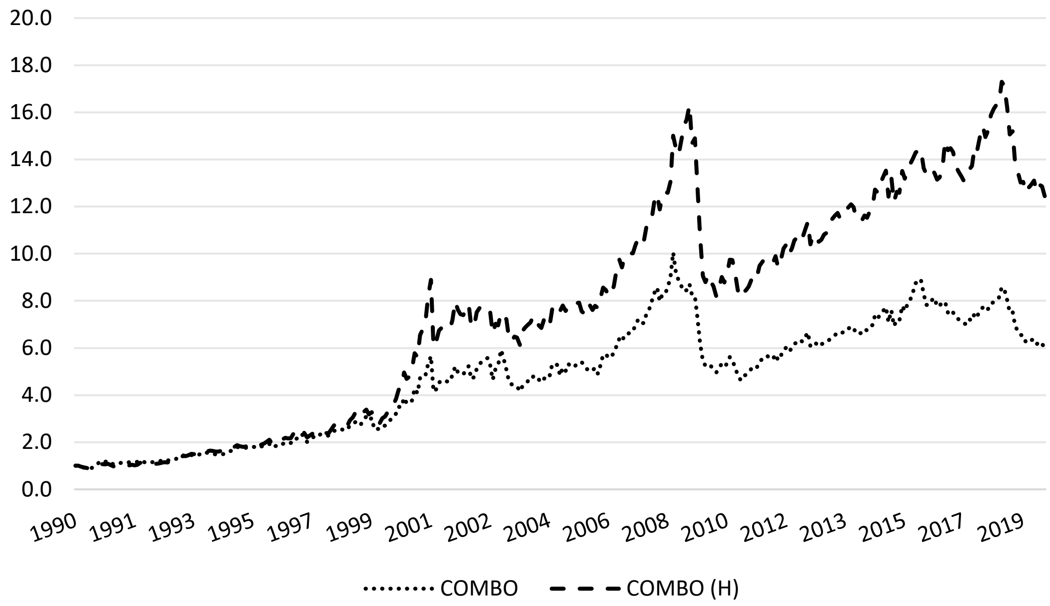

Figure 10. Portfolio cumulative returns

The unhedged (hedged) portfolio poses an average annualized return of 7.30% (9.86%) over the entire sample, both of which are significant at the 1% level. Such average returns are still below the returns on EQMOM and EQMOM (H) strategies, but the difference is not statistically significant. However, as earlier, the lower average returns lead to much higher total returns over the sample, due to a much lower number of extreme drawdowns. A single dollar invested in the COMBO (COMBO (H)) portfolio would cumulate to $6.04 ($12.44) over the entire 30-year period, outperforming both EQMOM and EQMOM (H) strategies. The unhedged (hedged) portfolio cumulative returns are illustrated in Figure 10**.**

Due to the low cross-strategy correlation for CFMOM and EQMOM (see previous chapter, table 8) the annualized volatility for the COMBO portfolio is at 15.87% (table 12 above), which is below the individual strategy volatilities of 18.06% (CFMOM) and 24.73% (EQMOM). When tested with the F-test, the COMBO portfolio volatility is lower than the volatility of the EQMOM strategy, the difference is significant at the 1% level. This leads to an increased Sharpe of 0.46 for COMBO, which is well above the EQMOM strategy Sharpe of 0.31 and slightly above the CFMOM strategy Sharpe of 0.40. The COMBO (H) portfolio also poses a volatility below either one of the individual hedged strategies at 16.57% vs. 18.65% (CFMOM (H)) and 25.46% (EQMOM (H)). As for the unhedged portfolio, the volatility of COMBO (H) is lower than the volatility of EQMOM (H), the difference is significant at the 1% level. This leads to a Sharpe of 0.59 for the COMBO (H) portfolio, a notable 0.12-0.14-point increase over the CFMOM (H) and EQMOM (H) strategies. However, the increases in Sharpe ratios for both portfolios COMBO and COMBO (H) over the EQMOM and EQMOM (H) strategies are not significant when tested with the Ledoit-Wolf (2008) test.

When comparing COMBO to the EQMOM strategy (table 12 above), the negative skewness and excess kurtosis are notably lower at -0.74 and 4.40 (down from -2.80 and 18.29). This becomes concrete when one examines the minimum and maximum monthly returns for the portfolio; the spread at -26.64% and +15.74% is much tighter and less skewed to the left when comparing to the EQMOM strategy spread of -59.95% and +19.30% (see previous chapter, table 8). The Momentum crash of January 2001 is dampened, as the COMBO portfolio "only" loses some 25% of its cumulative returns during this period compared to the EQMOM crash of 59.95%. However, the magnitude of the loss at -26.64% is larger than one third (portfolio weight of the EQMOM) of the EQMOM drawdown of -59.95%. This is due to the CFMOM strategy experiencing a loss of 10.00% during the same month. Regardless of diversification, the COMBO portfolio still experiences a severe crash during the Financial Crisis, losing 48.7% of its cumulative returns between July 2008 and November of 2009. Overall, COMBO experiences only 7 occurrences of drawdowns larger than 10%, which is a clear improvement from the earlier number of large drawdowns on the individual strategies (10 for CFMOM and 17 for EQMOM). The difference in the occurrence of large drawdowns between COMBO and EQMOM is significant at the 1% level.

The findings on skewness and kurtosis (table 12) are similar for the COMBO (H) portfolio at values of -1.05 and 7.10, which are notably lower than the skewness and kurtosis of -2.73 and 19.62 for the EQMOM (H) strategy. The worst monthly drawdown for COMBO

(H) portfolio is 31.93%, which is a clear improvement from the -63.97% of EQMOM (H) strategy. However, as for the unhedged strategies, the CFMOM (H) strategy also poses a negative return of -10.30% for January of 2001, thus diminishing the diversification benefits. The portfolio loses 43.42% of its cumulative returns between the same time span of July 2008 and November of 2009. However, the COMBO (H) portfolio peaks in early January of 2009, some five months later than its unhedged counterpart. From its peak, COMBO (H) experiences a drawdown of 49.84%. Overall, COMBO (H) experiences 8 occurrences of drawdowns larger than 10%, which equals the large drawdowns the CFMOM (H) strategy while being well below the number of drawdowns for the EQMOM (H) strategy (14). The difference in the occurrence of large drawdowns between COMBO (H) and EQMOM (H) is significant at the 5% level.

7.2.1 Subsamples

The descriptive statistics of the portfolios for the subsamples are illustrated in Table 15.

Table 15. Portfolio subsamples

	μ p.a. (%)	t-stat	σ p.a. (%)	R2R	Worst 6m (%)	Best 6m (%)	Skew	Kurt	μ p.a. diff. EQMOM
Period A: 01/1990-12/1999									
COMBO	*13.55*	(3.11)	*13.76*	*0.98*	*-14.53*	*32.35*	*-0.40*	*3.43*	*-0.78*
COMBO (H)	*15.41*	(3.60)	*13.53*	*1.14*	*-14.46*	*39.98*	*-0.41*	*0.88*	*1.71*
Period B: 01/2000-12/2006									
COMBO	*11.38*	(1.69)	*21.30*	*0.53*	*-26.16*	*40.47*	*-0.88*	*4.07*	*6.08**
COMBO (H)	*14.96*	(2.07)	*22.84*	*0.66*	*-23.86*	*59.40*	*-1.30*	*7.36*	*-0.13*
Period C: 01/2007-12/2009									
COMBO	*-5.12*	(0.87)	*18.59*	*-0.28*	*-39.80*	*21.14*	*-0.78*	*0.78*	*18.65*
COMBO (H)	*-0.77*	(0.11)	*21.52*	*-0.04*	*-46.03*	*22.57*	*-0.91*	*1.72*	*16.85*
Period D: 01/2010-12/2014									
COMBO	*7.58*	(2.40)	*10.00*	*0.76*	*-13.65*	*13.87*	*-0.92*	*1.23*	*-5.12*
COMBO (H)	*8.35*	(2.48)	*10.64*	*0.78*	*-13.34*	*19.05*	*-0.81*	*0.90*	*-5.59*
Period E: 01/2015-12/2019									
COMBO	*-3.71*	(0.92)	*12.78*	*-0.29*	*-22.86*	*22.46*	*-0.27*	*0.16*	*-14.80*
COMBO (H)	*-0.51*	(0.13)	*12.59*	*-0.04*	*-23.96*	*16.12*	*-0.25*	*0.40*	*-17.12*

The last column of the table compares the unhedged (hedged) portfolio mean annualized return over the selected period to the return of the respective unhedged (hedged) equity strategy. **Note:** *, ** and *** denotes significance at the 10%, 5% and 1% levels.

During the first ten-year period, the COMBO (COMBO (H)) portfolio annualized returns are at their highest at 13.55% (15.41%). This is slightly lower (higher) than the EQMOM and EQMOM (H) strategy annualized returns of 14.33% and 13.70% during the same period (please see chapter 8.1.1, table 10 for the descriptive statistics on the individual equity/commodity futures momentum strategies during the same subperiods). However, the portfolios pose annualized volatilities of 13.76% (COMBO) and 13.53% (COMBO (H)) for this period, both of which are well below the respective equity momentum strategy volatilities of 17.24% (EQMOM) and 19.46% (EQMOM (H)). This leads to a notable increase in Sharpe, which is now 0.98 (1.14) for COMBO (COMBO (H)) portfolio. The worst six-month drawdowns at -14.53% (COMBO) and -14.46% (COMBO (H)) are notably lower when comparing to the individual strategies which range between -20.49% (EQMOM) and -26.81% (EQMOM (H)). This is visible in the return distribution where unhedged portfolio poses lower negative skewness (-0.40) than either one of the individual strategies at -0.84 (EQMOM) and -0.56 (CFMOM).

The COMBO (COMBO (H)) portfolio returns 11.38% (14.96%) annualized over the 2000-2006 period. During this period, the COMBO portfolio’s annualized return is 6.08% higher than the return on the EQMOM strategy, this difference is significant at the 10% level. Additionally, at 21.30% (22.84%) annualized both portfolio volatilities are lower than any of the individual hedged or unhedged strategies’ volatilities ranging between 21.67% (CFMOM) and 36.01% (EQMOM (H)). Additionally, the return distributions for both portfolios pose much lower negative skewness and excess kurtosis when comparing to the respective equity momentum strategies.

Both portfolios pose negative returns for the crisis period. The immense melt-up of 2007-2008 makes the COMBO (H) portfolio average near zero returns at -0.77% annualized. However, during this period, the cumulative return for the unhedged (hedged) portfolio is -20.20% (-9.70%), which is still an improvement from the equity momentum strategies’ returns of -65.10% (EQMOM) and -61.40% (EQMOM (H)) As earlier, the negative skewness is notably smaller for the portfolios.

Post-crisis both portfolios pose lower returns than their equity counterparts at 7.58% (COMBO) and 8.35% (COMBO (H)). However, during this five-year period, the portfolio volatilities are on a low level of 10.00% for the unhedged and 10.64% for the hedged portfolio, respectively. The poor performance culminates in the most recent five-year period, where both portfolios realize negative annualized returns. This is unsurprising considering the high weight of the commodity strategy and its sudden downturn since early 2018. In hindsight, an investor would be better off investing in the pure equity momentum strategies post-crisis, as their Sharpe ratios and returns are much higher. The recent underperformance of the commodity strategy raises many questions; could the swift change in global monetary policy post crisis affect the returns – or could the underperformance arise from the *"financialization"* of commodity markets?

7.2.2 Portfolio Regressions

Table 16 presents the modified FF3 and FF6 regression results on the portfolios. The difference between the portfolio and the respective unhedged (hedged) equity strategies' annualized alphas and factor exposures are presented in the rightmost two columns. Again, the heteroskedasticity consistent t-statistics are reported in the parentheses.

Table 16. Portfolio FF3 and FF6 regressions

	COMBO	***COMBO (H)***	***Difference COMBO - EQMOM***	***Difference COMBO (H) - EQMOM (H)***
Panel A: Fama-French Three Factors and GSCI				
Alpha (%)	***8.7****	***11.2****	***-2.4***	***-1.8***
	(3.03)	(3.66)	(1.60)	(1.09)
GSCI	*0.145***	*0.033*		
	(2.19)	(0.53)		
Mkt	*-0.186****	*-0.188****	*0.136*	*0.048*
	(2.76)	(2.44)	(1.01)	(0.33)
SMB	*-0.036*	*0.084*	*0.176*	*-0.003*
	(0.30)	(0.62)	(0.74)	(0.01)
HML	*-0.161*	*-0.026*	*0.159*	*-0.175*
	(1.47)	(0.20)	(0.64)	(0.63)
R2	*0.05*	*0.03*		
Panel B: Fama-French Six Factors and GSCI				
Alpha (%)	***1.5***	***3.2***	***5.2****	***5.1****
	(0.56)	(1.13)	(4.05)	(4.30)
GSCI	*0.112***	*-0.005*		
	(2.10)	-(0.10)		
Mkt	*0.089*	*0.129**	*-0.122*	*- 0.189**
	(1.46)	(1.84)	(1.16)	(1.94)
SMB	*-0.002*	*0.092*	*0.147*	*-0.008*
	(0.02)	(0.95)	(1.05)	(0.06)
HML	*-0.054*	*0.029*	*-0.125*	*-0.397****
	(0.57)	(0.27)	(0.74)	(2.47)
RMW	*0.229**	*0.185**	*-0.229*	*-0.159*
	(1.92)	(1.29)	(1.38)	(0.86)
CMA	*0.184*	*0.385***	*0.131*	*0.017*
	(1.21)	(2.14)	(0.49)	(0.07)
UMD	*0.575****	*0.633****	*-0.714****	*-0.644****
	(8.65)	(7.76)	(5.31)	(6.59)
R2	*0.39*	*0.40*		

Note: *, ** and *** denotes significance at the 10%, 5% and 1% levels.

Both portfolios pose positive significant alphas at the 1% level when regressed against the modified FF3 model. Similar to the regressions on the individual momentum strategies, the COMBO (H) portfolio poses a higher alpha at 11.20% annualized while COMBO poses a notable alpha of 8.70%. Both alphas are still below those of the individual equity momentum strategies - however, the difference is too small to draw any statistical significance. Only the unhedged portfolio poses a significant exposure to the GSCI. Notably, the market exposures for the portfolios are on a much lower level than for the individual equity momentum strategies. The COMBO (COMBO (H)) portfolio has a beta of -0.186 (-

0.188) towards the overall market, both down from the earlier exposure of -0.322 (-0.236) for the EQMOM (EQMOM (H)) strategy. The exposures to the other FF3 factors are insignificant and as for the individual momentum strategies, the model does a poor job at explaining the portfolio returns with the R-squared statistics remaining in the sub 0.05 territory.

Neither of the portfolio alphas are significant when regressed against the modified FF6 model. However, as their sign is positive, the difference between these and the equity momentum strategies' alphas becomes significant at the 1% level. The COMBO portfolio retains its relatively small but significant exposure to the GSCI at a beta coefficient of 0.112. As with the individual momentum strategies, the market exposures for the two portfolios are positive. However, only the COMBO (H) poses a significant exposure to the overall market at 0.129. Overall, when comparing the hedged portfolio to EQMOM (H), the hedged portfolio is much less exposed to the performance of the equity markets, with the difference being significant at the 10% level. Both portfolios have slight exposures towards the RMW factor with betas of -0.229 and 0.185. These exposures are still well below those of the individual equity momentum strategies' betas, but statistically the difference remains insignificant. The hedged portfolio poses a significant positive beta of 0.385 towards the CMA factor, which is roughly at the level of the exposures of EQMOM (H) and CFMOM (H). The portfolios retain their positive exposure to the UMD factor. As earlier, the modified FF6 model manages to adequately explain the returns with its R-squared statistics being at 0.39 (0.40) for the unhedged (hedged) portfolio.

Table 17 contains the results of an optionality regression used to uncover the strategies' behaviour during and after bear markets (Daniel & Moskowitz, 2016; Grobys, 2016). The market variable is the same as earlier. The Bear variable gets a value of one if the preceding 24-month market return is negative and is a zero otherwise. The Bull variable gets a value of one if the current month return is positive. Thus, the third coefficient captures the strategy (portfolio) behaviour during post bear market reversals.

Table 17. Optionality regressions

	EQMOM	***CFMOM***	***COMBO***	***COMBO***	***COMBO***
Panel A: Strategies & portfolio					
Intercept	*0.012****	*0.008****	*0.010****	*0.009****	*0.010****
	(3.09)	(3.13)	(3.72)	(3.49)	(3.93)
Mkt	*0.060*		*-0.039*		*-0.036*
	(0.60)		(0.59)		(0.60)
Bear * Mkt	*-0.310*		*0.050*		*-0.207*
	(1.31)		(0.32)		(1.41)
Bear * Bull * Mkt	- *1.274****		- *0.800****		- *0.362**
	(4.01)		(3.78)		(1.81)
GSCI		*0.478****		*0.346****	*0.362****
		(9.64)		(7.58)	(7.90)
Bear * GSCI		- *0.680****		- *0.483****	- *0.474****
		(5.93)		(4.58)	(4.62)
Bear * Bull * GSCI		- *0.307***		- *0.307***	- *0.256**
		(2.07)		(2.25)	(1.90)
R2	*0.14*	*0.27*	*0.07*	*0.20*	*0.25*
Panel B: Hedged stratgies & portfolio					
	EQMOM (H)	***CFMOM (H)***	***COMBO (H)***	***COMBO (H)***	***COMBO (H)***
Intercept	*0.016****	*0.011****	*0.012****	*0.012****	*0.014****
	(3.87)	(3.77)	(4.53)	(4.49)	(5.03)
Mkt	*-0.130*		*-0.096*		*-0.078*
	(1.21)		(1.38)		(1.15)
Bear * Mkt	*0.197*		*0.127*		*-0.044*
	(0.78)		(0.77)		-(0.27)
Bear * Bull * Mkt	- *1.345****		- *0.800****		- *0.474***
	(3.97)		(3.61)		(2.13)
GSCI		*0.221****		*0.175****	*0.184****
		(3.96)		(3.46)	(3.59)
Bear * GSCI		- *0.379****		- *0.212**	- *0.205**
		(2.94)		(1.82)	(1.79)
Bear * Bull * GSCI		- *0.452****		- *0.457****	- *0.389****
		(2.71)		(3.04)	(2.58)
R2	*0.07*	*0.13*	*0.06*	*0.10*	*0.14*

Panel A summarizes the regression results for EQMOM, CFMOM and the constructed combination portfolio COMBO. **Panel B** summarizes the regression results for the **hedged** strategies EQMOM (H), CFMOM (H) and the combination portfolio constructed from the hedged strategies COMBO (H). **Note:** *, ** and *** denotes significance at the 10%, 5% and 1% levels.

Like the findings of Daniel and Moskowitz (2016), the EQMOM strategy poses a high coefficient towards the market reversal variable. However, in this sample the bear market coefficient is insignificant for both unhedged and hedged equity momentum strategies. During post bear market reversals, the equity momentum strategies return -1.274 (EQMOM) and -1.345 (EQMOM (H)) times the overall market return, thus acting effectively like short call options on the overall market.

Based on the regression, the CFMOM and CFMOM (H) strategies gain during GSCI bear markets as the sum of the two first beta coefficients are -0.202 (-0.158) for the CFMOM (CFMOM (H)) strategy. The commodity futures momentum strategies face the same problem as their equity momentum counterparts: during post bear market reversals, the three significant strategy betas sum up to -0.509 for the CFMOM and -0.610 for the CFMOM (H) strategy. Thus, if the market reverses 10% after a bear market, the strategies on average lose between 5.1% and 6.1%.

The right most column regresses the constructed portfolios on all the variables, providing the highest R-squared values. As earlier, the bear market coefficient towards the equity markets remains insignificant. During GSCI bear markets, the unhedged (hedged) portfolio beta towards the GSCI is -0.112 (-0.021). The COMBO and COMBO (H) portfolios pose a beta of -0.362 (-0.474) towards the equity market reversal variable, substantially down from the earlier values of -1.274 and -1.345 for EQMOM and EQMOM (H). However, these coefficients are not directly comparable due to the GSCI variables included in the regression. When comparing COMBOs to EQMOMs regressions *using only the equity market variables* (the fourth column), the equity market reversal coefficient experiences a 37% (40%) reduction to -0.80 (-0.80). This reduction in the equity market reversal coefficient is much smaller than the weight of the EQMOM and EQMOM (H) in the portfolios would suggest. Further examining the full regression for COMBO and COMBO (H) (the last column including all variables), the coefficient towards the GSCI market reversal experiences a 17% (14%) reduction to -0.256 (-0.389) when compared to the regressions on CFMOM and CFMOM (H). Overall, the portfolios pose a beta of -0.368 (-0.410) towards the GSCI during these reversals, some 28% (33%) down from the earlier values of -0.509 (-0.610) for CFMOM and CFMOM (H).

During the whole sample period of 30 years, the post bear market reversal variable gets a value of one 80 times for the GSCI and 29 times for the equity market. The simultaneous activation of these variables is of interest when considering the possible diversification benefits. The two variables have 13 occurrences of simultaneously getting a value of one. 11 of these occurrences happen between March of 2009 and September of 2010, during the same time the equity strategy experiences its disastrous crash. In aggregate, the unhedged (hedged) portfolio loses 33% (35%) of its cumulative returns during this period of 19 months. Thus, it seems that one can slightly dampen, but not fully remove the optionality embedded within the strategies through the diversification process.

Lastly, a regression is run to uncover whether the portfolios are less exposed to overall equity market risk (measured as volatility) and liquidity risk. Table 18 presents the regression results obtained from regressing all the strategies and both portfolios on the TED spread and the VIX-index over the full sample and a subsample containing the years of the Financial Crisis (2007-2009).

Table 18. Liquidity and volatility regressions

	EQMOM	***CFMOM***	***COMBO***	***Diff. (COMBO - EQMOM)***
Panel A: Strategies & portfolio				
Whole sample				
TED	*0.022***	*0.012*	*0.015**	*-0.007*
	(2.00)	(1.19)	(1.78)	(0.49)
VIX	*-0.034*	*-0.007*	*-0.016*	*0.018*
	(0.86)	(0.28)	(0.67)	(0.38)
01/2007-12/2009				
TED	*0.075***	*0.002*	*0.026**	*-0.049*
	(2.46)	(0.14)	(1.74)	(1.43)
VIX	- *0.363***	*-0.019*	- *0.134***	*0.229*
	(2.38)	-(0.35)	(2.08)	(1.38)
Panel B: Hedged strategies & portfolio				
Hedged, Whole sample				
TED	*0.023***	*0.026****	*0.025****	*0.002*
	(2.45)	(3.12)	(3.89)	(0.15)
VIX	*-0.029*	*-0.031*	*-0.030*	*-0.002*
	(0.73)	(1.26)	(1.31)	(0.03)
Hedged, 01/2007-12/2009				
TED	*0.085****	*0.014*	*0.043****	*-0.042*
	(3.22)	(1.13)	(3.21)	(1.42)
VIX	- *0.400****	*-0.020*	- *0.174***	*0.226*
	(2.58)	(0.33)	(2.27)	(1.31)

Panel A summarizes the regression results for EQMOM, CFMOM and the combination portfolio COMBO. **Panel B** summarizes the regression results for the **hedged** strategies EQMOM (H), CFMOM (H) and the hedged combination portfolio COMBO (H). **Note:** *, ** and *** denotes significance at the 10%, 5% and 1% levels.

Over the entire sample, both EQMOM and EQMOM (H) pose positive exposures to the TED spread. This means that during this sample, the equity momentum strategy returns increase as the overall market liquidity decreases, which supports the findings of Butt and Virk (2017). The EQMOM and EQMOM (H) exposures to VIX are insignificant over whole sample. CFMOM is not affected by fluctuations in the VIX nor in the TED spread. However, CFMOM (H) poses a highly significant positive exposure to the TED spread.

During the Financial Crisis, both EQMOM and EQMOM (H) have their exposure towards the TED spread grows more than threefold. During the crisis years, the TED spread widened quickly as the overall market liquidity started to evaporate. As discussed in Chapter 5.2.1., this leads to a flight to quality phenomena, which in turn causes the winner portfolio to pose substantial returns as the past losers crash harshly (Butt and Virk, 2017). However, after peaking in September of 2008, the spread starts shrinking quickly with various Central Bank interventions. As the TED spread shrinks, the equity strategies experience their disastrous downturns of early 2009 already discussed earlier in this chapter. During this time, a 1bps increase (decrease) in the TED spread would lead to a 0.075% (0.085%) increase (decrease) in average monthly returns for the unhedged (hedged) equity momentum strategy. The increase may seem small, but one must consider that the TED spread increases from a low of 34bps (February 2007) to a high of 315bps (September 2009) during the crisis. Interestingly, both commodity futures momentum strategies are unaffected by the fluctuations in the TED spread during the crisis period.

EQMOM and EQMOM (H) exposures to the VIX become highly significant within crisis period. The unhedged (hedged) strategy poses a beta of -0.363 (-0.400) towards the VIX during this period. Thus, rapidly increasing market volatility leads to the strategies experiencing large losses, which directly supports the notion of the option-like behaviour of the short leg proposed by Daniel and Moskowitz (2016). A monthly jump on the VIX-index of 20 points (for example from 20 to 40 during August-September of 2008) would on average lead to monthly losses of -7.26% (-8.00%) for the unhedged (hedged) strategy.

Over the whole sample, both COMBO and COMBO (H) have a positive and a significant exposure towards the TED spread at coefficients of 0.015 for COMBO and 0.025 for COMBO (H), respectively. As with the individual momentum strategies, neither of the portfolios pose a significant relation towards the VIX-index. The unhedged (hedged) portfolio poses a beta of 0.026 (0.043) towards the TED spread during the Financial Crisis, down 0.049 (0.042) from the Beta exposures of EQMOM (EQMOM (H)). Additionally, the portfolio exposures towards the VIX-index during this time are notably smaller at -0.134 for the unhedged and -0.174 for the hedged strategy, respectively. However, due to high standard errors, none of these seemingly large differences are statistically significant.

8 Conclusions

Commodity futures are often considered a highly volatile asset class. However, due to their attractive returns and low correlation with other investment vehicles, they are considered a prominent tool for portfolio diversification (Jensen et al. 2000). Momentum is a phenomenon witnessed globally in various financial asset classes for more than two hundred years (Asness et al. 2014). Equity momentum strategies often pose higher volatility than the underlying equity indices they are based on. However, due to the strategy market neutrality and above average excess returns, the performance of momentum strategies is largely left unexplained by regular risk factor models (Jegadeesh & Titman, 1993; Ruenzi & Weigert, 2018). However, equity momentum strategies are prone to disastrous crashes, which is present as high negative skewness and excess kurtosis in the strategy return distributions (Daniel & Moskowitz, 2016; Ruenzi & Weigert, 2018). Momentum strategies implemented on commodity futures pose statistically significant excess returns with promising Sharpe ratios found between 0.40-0.70 (Miffre & Rallis, 2007). Additionally, the strategies pose low correlations towards their equity counterparts (Asness et al. 2014).

The purpose of this thesis is to examine whether the diversification benefits obtained from including commodity futures in regular portfolios holding only long positions are applicable to momentum strategies implemented on these two asset classes. This is examined by reviewing the differences between strategy-portfolio average annualized returns, Sharpe ratios and annualized alphas. Additionally, this thesis examines whether the diversified portfolios are less prone to crash risk. This is examined by optionality regressions first proposed by Daniel and Moskowitz (2016). The portfolio-strategy behaviour in extreme market conditions is also examined through regressions against overall equity market risk (VIX) and market liquidity (TED spread).

The first research hypothesis concerned the excess returns of the commodity futures momentum strategies. The hypothesis is accepted for the whole sample as the commodity futures momentum strategies produce statistically significant excess returns.

However, towards the end of the sample the two commodity futures momentum strategies pose insignificant or negative returns. Thus, it remains to be seen whether the days of glory are over for commodity futures momentum investing.

Both of the constructed portfolios pose significantly lower annualized volatilities when compared to the pure equity momentum strategies. This finding is similar to the earlier findings on regular commodity-equity portfolios (Jensen et al. 2000), suggesting that the risk diversifying ability of commodity futures is applicable in momentum investing. Nonetheless, there is no statistical difference in the mean returns nor in the Sharpe ratios between the individual strategies and the portfolios. However, the total cumulative returns on the portfolios are nearly 90% (35%) higher for the unhedged (hedged) portfolios. Thus, one can argue that the statistical tests for the difference in mean returns or the Sharpe ratios do not tell the whole story. Additionally, the diversified portfolios experience a significantly lower number of large (>10%) drawdowns when comparing to the pure equity momentum strategies, with the differences being statistically significant at the 1% and 5% levels. This is present in the portfolio return distributions, which pose notably lower negative skewness and excess kurtosis when comparing to the pure equity momentum strategies. The low number of large drawdowns is a major contributor to the superior cumulative returns.

Neither of the portfolio alphas significantly differ from the alphas of the equity strategies when corrected for the FF3 factors. The FF6 regressions reveal a significant difference of some 5% annualized in favour of both portfolios. However, it should be highlighted that individually neither of the portfolio alphas are significant when corrected for the FF6 factors. Furthermore, the diversified portfolios are less exposed to several of the risk factors, such as the market, HML, RMW, CMA and UMD factors.

The constructed portfolio exposures towards the equity market volatility (VIX) and overall market liquidity (TED spread) do not statistically differ from those posed by the equity strategies, even though the individual commodity futures strategies are not exposed to these risk factors.

However, regardless of the improved cumulative returns and other potential benefits, the second hypothesis concerned the potential improvement in risk adjusted return and strategy alpha. Thus, based on the evidence the hypothesis is rejected, the performance of the diversified portfolios does not statistically differ from the pure equity momentum strategies' performance.

When examining the cumulative return graphs, one could conclude that the diversified portfolios are still subject to severe crashes. The individual commodity futures momentum strategies experience negative returns during the same months the equity strategies crash. This finding is approved by the optionality regressions, which find the portfolios still posing substantial negative total exposures to the equity and commodity markets during post bear market reversals. Thus, the final hypothesis is rejected; portfolio diversification has no effect on the momentum crashes experienced during times of market distress.

8.1 Suggestions for Further Research

The performance of the commodity futures momentum strategy experiences a sudden change after the Financial Crisis. The cause of this change could possibly originate from the financialization of the commodity futures markets or some other macro factors, such as changes in the level of global inventories. Further research could try to shed some light on this sudden pivot in the strategy performance. Additionally, as this thesis uses monthly data and as it had no access to the long and short legs of the commodity strategy, it could not take advantage of other risk management methods, such as volatility scaling. Further research could examine the correlations between the commodity and equity strategies' long and short legs in addition to examining the performance of volatility managed commodity futures momentum strategies and dual momentum portfolios.

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